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RESEARCH ARTICLE

Occupational licensing and income inequality in the states

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Abstract

The decades-long rise of economic inequality in the U.S. has led to a growing body of literature examining the role of policy in shaping income differences. We examine one such policy: occupational licensing regulations. Licensing can restrict employment and reduce market competition, which can then inflate wages for those in licensed professions. Existing research demonstrates that occupational licensure does increase wages in specific industries, leading some scholars to argue that licensing makes income inequality worse. We add nuance by arguing that the effect of licensing on inequality is dependent on which occupation classes experience the largest wage premiums. Using a comprehensive over-time database of state licensing regulations, we first demonstrate that medium- and low-wage jobs garner larger wage premiums than high-wage occupations. Second, consistent with this result we then show that the occupational licensing regulations have the overall effect of reducing state income inequality. This research contributes to our understanding of the causes of growing inequality and how public policy can shape economic disparities through sometimes unintended and indirect ways.

INTRODUCTION

As economic inequality in the U.S. has continued to grow, scholars have examined how politics and policy play a role in rising income differences (Bartels, 2008; Hacker & Pierson, 2010). This work has fruitfully examined national (Enns et al., 2014; Kelly, 2020; Smeeding, 2005; Witko et al., 2021) and state (Franko & Witko, 2017; Kelly & Witko, 2012; Langer, 2001) fiscal and redistributive policies that affect top and bottom income shares in ways that exacerbate inequality (Hayes & Vidal, 2015; Jansa, 2020; Kelly, 2009). Beyond these "usual suspects," others have hypothesized that other governmental policies meant to condition labor markets can have unintended consequences for inequality (Lindsey & Teles, 2017). We examine one such policy that may play a role in creating (or curbing, as we will see) state-level income inequality: occupational licensing regulations.

Licensing regulations have been largely overlooked as a potential determinant of aggregate inequality in the United States.[1] This is despite a growing academic (Gittleman et al., 2018; Kleiner & Krueger, 2010; Kleiner & Vorotnikov, 2017) and policy (e.g., National Conference of State Legislatures, 2020) interest in occupational licensing itself. For example, each of the past three presidential administrations have published comprehensive reports on occupational licensing, with suggestions for welfare enhancing reform.[2] Crucially, though, occupational licensing is a policy area squarely in the purview of the state governments, so federal policy can only signal intent and support/convince state governments to change policy in this area. This fact can give us empirical leverage on the effects of within-state licensing changes over time, which is the primary empirical approach we take below. Furthermore, there are plausible mechanisms by which occupational licensing could either exacerbate or actually reduce trends in economic inequality, depending on where in occupational income distributions licensing produces wage premiums.

In this research, we describe these mechanisms and the primary condition that determines whether state-level licensing regulations should be expected to degrade or improve state levels of income inequality. In particular, expectations regarding the effects of occupational licensing regulations for the shape of income distributions hinge on whether or not such rules produce wage premiums for those in licensed professions and on where these premiums exist in occupational wage distributions. If and when wage premiums exist primarily for high-wage occupations, licensing should be expected to increase income inequality. However, if such premiums exist most broadly for low- and medium-wage occupations, then licensing regulations actually have the potential to reduce aggregate inequality (especially if licensing mandates are increasingly concentrated in low- and medium-wage sectors).[3]

In subsequent sections, we review the conventional wisdom regarding wage premiums that may result from licensing regimes. We conclude that while considerable evidence exists of wage premiums, existing research does not adequately describe the types of occupations that benefit most from such wage premiums. Thus, we go on to empirically assess whether licensing generates broad-based wage premiums and find that it generally does not for high-wage occupations but does for low- and medium-wage occupational classes. Therefore, we proceed to examine the relationship between licensing coverage and state inequality with the hypothesis that increased regulation serves to *reduce* inequality in the states (by increasing the share of the income distribution that goes to low- and medium-wage licensed workers). Finally, using different indicators of state-level inequality, we infer that this relationship operates by both raising middle income shares and reducing top income shares.

Our research promises to inform the normative debate regarding the costs and benefits of licensing regulations. Licensing does not uniformly affect inequality in either direction and a great deal of the effect is determined by whether a licensing regime produces significant wage premiums at particular points of occupational wage distributions. This is a fact that is significantly underappreciated by previous research. In addition, our work contributes to a growing understanding of the nuances of

[1] Though previous work has examined the effect of licensing on within occupation wage dispersion (Kleiner & Krueger, 2013) and across different quantiles of the wage distribution (Gittleman et al., 2018). Still, no existing work explores whether licensing laws affect statewide wage distributions as we pursue in this study. Most recently, Dodini (2023) examined similar outcomes to ours as a function of licensing spillover and Haupt (2023) studied the effects of licensing on wage inequality within demographic groups.

[2] Perhaps surprisingly, each of the Obama, Trump, and Biden administrations advocated (with varying degrees of zeal) for licensing reforms that would loosen labor market regulations, especially for certain populations (veterans and military spouses, for example; Council of Economic Advisers, 2020, 2022; White House, 2015).

[3] This is an aggregate view of the effects of licensing on overall inequality. Previous research (Kleiner & Krueger, 2013) has found that licensing serves to increase inequality within occupations via exclusive wage premiums. As described below, our data measures legal licensing coverage in aggregate, so we cannot identify individual licensed and unlicensed workers. Nevertheless, we expect that differential wage premiums for different types of occupations should have implications for aggregate inequality that are distinct from the within-occupation effects found by Kleiner and Krueger (2013), for example.

economic inequality and how public policy may serve to affect economic inequality through market conditioning.

STATE INEQUALITY AND OCCUPATIONAL LICENSING

Economic inequality is a salient topic of concern for economists, public policy scholars and makers, and for the citizens who work and live in polarized societies. From a purely economic perspective, inequality has many causes, including skill-biased technology changes (Acemoglu & Autor, 2011; Autor et al., 1998; Card & DiNardo, 2002), globalization (Bergh & Nilsson, 2010; Helpman, 2016), and deregulation (Fortin & Lemieux, 1997; Kim & Sakamoto, 2008). Public policy decisions have also contributed heavily to economic inequality (Bartels, 2008; Hacker & Pierson, 2010; Kelly, 2009; Piketty & Saez, 2003; Smeeding, 2005). Relevant policy changes have led to declining minimum wages (Autor et al., 2016), reduced unionization (Ahlquist, 2017; Western & Rosenfeld, 2011), and changes in organizational practices (Cobb, 2016) that may contribute to widespread wage polarization and income inequality.[4]

This line of work also uncovers how economic disparities are shaped by policy choices that are less visible than the more obvious redistribution programs. Hacker and Pierson (2010) argued that the current state of American income inequality is at least in part related to the concerted efforts of wealthy interests to deregulate markets, allowing financial executives to increase their profit shares (also see Keller & Kelly, 2015; Lindsey & Teles, 2017). While reducing the size of government through tax cuts was also part of these efforts, the rich received the largest cuts (also see Faricy, 2015). Of course, a smaller government also means fewer or scaled down public programs (Adolph et al., 2020).

While the federal government is often examined when assessing the influence of policy on inequality, the states also have the power and resources to shape the localized income distributions. This is particularly true in the context of our contemporary politics where the U.S. Congress has regularly been unwilling or unable to address expanding inequality (Enns et al., 2014; Hacker & Pierson, 2010). The states can influence inequality through traditional redistributive policies like higher taxes on the rich and spending more on welfare programs (Franko et al., 2016; Hatch & Rigby, 2015; Hayes & Vidal, 2015; Kelly & Witko, 2012), as well as through policies that shape pre-redistribution income like union membership and increasing the minimum wage (Franko & Witko, 2017; Meszaros, 2018; Volscho & Kelly, 2012). We extend this research with a novel focus on the potential effects of state occupational licensing regulations. While proponents of licensing regimes do not necessarily intend these policies to affect wage and income inequality, there are good theoretical reasons to suspect that they do.

Licensure laws establish standards that must be met in order for an individual to practice a given profession. The requirements for obtaining a license vary among occupations, but many require formal education, proof of experience or apprenticeship, formal exams, regular dues or fees, strong moral standing within the community, and citizen or residency provisions (Kleiner, 2006).

The most common justification for requiring licensure in a given profession is that it will increase the quality of the good or service being provided (Leland, 1979; Shapiro, 1986). Proponents of licensing laws suggest they can also benefit consumers by decreasing uncertainty and providing better information about the goods and services they purchase (Carroll & Gaston, 1981; Feldman & Begun, 1985). Evidence supporting these claims, however, is thin (for an overview, see Lindsey & Teles, 2017). Furthermore, even if there are such benefits to licensing, licensure undoubtedly produces higher

[4] Wage inequality refers to disparities in earnings among individuals for their labor. Income inequality encompasses a broader spectrum, including not only wages but also other sources of income such as investments, capital gains, and benefits. Some determinants affect wages more than income (e.g., varying minimum wage laws) and some affect income more than wages (e.g., varying social safety nets). We contend that licensing regulations can affect income inequality through their effects on wages.

costs that are passed on to consumers.[5] Of course, consumers may be willing to pay more for increased quality and better product information, but this will at least partly depend on the realized benefits created by licensing requirements.

Regardless of the effectiveness of licensing and the balance of consumer benefits and costs it produces (this aspect of occupational licensure is not fundamental to our research), licensure requirements have grown dramatically in recent years. In 1950, just 5% of Americans were employed in licensed professions. This number climbed to 30% by 2008 (Kleiner & Krueger, 2013). Growing far beyond doctors, lawyers, and engineers, many states currently require occupational licenses for cremation and funeral services (Harrington & Krynski, 2002), hair braiding (Bergal, 2015), and interior design (Harrington & Treber, 2009). Since the rise of licensing requirements has been driven in part by the passage of state laws (see note 19 below), it is also the case that the proportion of licensed workers varies substantially across the states. In Iowa, Nevada, and Washington, for example, over 30% of the workforce is in licensed professions, while under 15% of workers are licensed in New Hampshire, Rhode Island, and South Carolina (Kleiner & Vorotnikov, 2017).[6]

A number of studies demonstrate that new licensing requirements often lead to inflated wages for those in licensed professions (Gittleman et al., 2018; Kleiner & Krueger, 2010; Kleiner & Vorotnikov, 2017). Occupational licensing is not accessible to all potential workers. Licensing boards often place limits on the number of licensed positions, and because a license can be difficult to obtain (e.g., high licensing fees, long training durations and testing, etc.), it is likely that some otherwise qualified candidates face barriers to entry and are prevented from entering these professions. This can create a market monopoly for those who are able to secure a license in a given domain, thereby leading to inflated wages for those in the licensed professions. Empirically, the creation of wage premiums for licensed jobs has been demonstrated using a number of different data sources and contexts. Kleiner and Krueger (2010, 2013) estimated cross-sectionally that wages for licensed positions are 10% to 15% higher than they are for comparable non-licensed positions. Using more fine-grained data on both licensing statutes themselves (rather than self-reports of license mandates) and longitudinal wage information, Gittleman and Kleiner (2016) estimated wage premiums closer to 5% (see also Gittleman et al., 2018, who came to a similar conclusion using Survey of Income and Program Participation data). Scholars have extended these findings beyond the U.S. and uncovered similar effects in Canada (Zhang & Gunderson, 2020) and in the European Union (Koumenta & Pagliero, 2019). On the whole, these studies provide convincing evidence in favor of wage premiums resulting from licensing.[7]

While these studies suggest that licensure requirements increase wages within particular occupations, they do not directly address whether more restrictive licensing requirements lead to overall higher levels of income inequality nor do they always estimate effects using within-occupation comparisons. On one hand, it seems likely that occupational licensing will create greater inequality when considering high-paying, largely licensed professions like the medical and legal fields. If the high-earning workers in these professions also enjoy a wage premium as a result of licensing requirements, they are almost certain to pull further away from low- and middle-income groups. This is indeed the stated expectation of Lindsey and Teles (2017), whose book subtitle reflects their view concisely: "How the Powerful Enrich Themselves, Slow Down Growth, and *Increase Inequality*" (emphasis ours). And, some existing work is consistent with this expectation. Using a quantile regression approach, Kleiner and Vorotnikov (2017) "suggest that licensing exacerbates relative income inequality, since higher wage occupations tend to gain more from the regulation relative to lower wage ones" (p. 150; also see Gittleman et al., 2018). Thus, *if licensing produces large wage premiums*

[5] Estimates show that licensing requirements led to $700 million in added costs for the dentistry profession (Shepard, 1978) and optometry licensing costs totaled $500 million in the U.S. (Cox & Foster, 1990). Benham and Benham (1975) estimated a 25% to 40% increase in the costs of optometry services, as well as a decrease in demand from consumers.

[6] See Figure A1 for a depiction of over-time state-by-state variation in licensing coverage.

[7] Redbird (2017), on the other hand, provided the heterodox argument that licensing can *increase* employment in regulated occupations, while having null effects on wages. Though, see Deyo et al. (2018) for a critique of this argument.

among high-wage occupations (and small or no wage premiums for medium- and low-wage occupations), then as licensing regulation increases within a state, so should economic inequality (Increasing Inequality Hypothesis).[8]

Yet, Kleiner and Vorotnikov (2017) did not examine differential wage premiums across different occupation types and made their inference based only on average effects of licensing on wage quantiles. They also did not directly assess whether licensing alters the income distribution. It is possible that wages respond differentially across different classes of jobs, with new licensing mandates having larger effects on more commonly held low- and medium-wage jobs than they do for high-wage occupations. Most anecdotal accounts of the wage distorting effects of licensing focus on very high-wage occupations, such as those found in medical fields (e.g., Lindsey & Teles, 2017). While it is likely true that licensing does have a causal effect on wages in such high-paying fields, these effects are empirically difficult to distinguish given how universal they are across the states and over time.

The fact that high-wage jobs have been saturated with licensing regulations (Lindsey & Teles, 2017) is indeed interesting for many research questions. However, between-occupation licensing wage premiums (Zhang & Gunderson, 2020) cannot explain within-state variation in income distributions without evidence that occupation mixes vary significantly in states over time. Thus, in the next section we focus entirely on within-occupation wage effects of the introduction of state licensing. Within-occupation, it is possible that wage premiums are larger for low- and medium-wage jobs than they are for high-wage jobs (Redbird, 2017).

As distinct from the *Increasing Inequality Hypothesis*, we also consider the effects that would result if low- and medium-wage jobs produce larger wage premiums than we find for the high-wage jobs (especially since we will demonstrate that much of the aggregate increase in licensing in the states come from new laws targeting low- and medium-wage occupations). Here, *if licensing produces large wage premiums among lower and medium wage occupations (and small or no wage premiums for high-wage occupations), then as licensing regulation increases within a state, economic inequality should decrease (Decreasing Inequality Hypothesis).* This hypothesis follows the same logic as the first: if wage premiums serve to disproportionately increase wages for those of the lower ends of state income distributions, increased licensing should be expected to reduce income inequality. Similar arguments apply to the effects of labor unionization on state income distributions: when wage premiums bolster lower wage earners, they compress existing income inequality (Ahlquist, 2017; Card et al., 2017).

On the other hand, while licensure requirements have grown steadily in recent years, the highest estimates show licensed professions make up around 30% of the overall workforce (Gittleman et al., 2018). Additionally, depending on the occupation being studied, estimates of the size of wage inflation resulting from license requirements range from 0 to 35% (Redbird, 2017, though also see Deyo et al. 2018). These points suggest that even if wage premiums are real, they may not be substantial enough in size or scope to shape overall levels of income inequality. In addition, if licensing creates similar wage premiums for all occupation types and the mix of occupation types in states stays roughly the same, then logically wage premiums would fail to change overall income distributions. Thus, *if licensing produces no (or very small) wage premiums (or if wage premiums are the same for all licensed occupations), then as licensing regulation increases within a state, there should be no effect on economic inequality (Null Inequality Hypothesis).*

With limited previous research to guide us, it is difficult to know ex ante which hypothesis is most likely to be supported in this scenario. On the one hand, it is likely true that licensing enacts entry restrictions that are more severe for higher wage occupations than they are for lower wage positions. These restrictions could directly lead to higher wage premiums or could do so through spillovers. For example, Zhang and Gunderson (2020) described that “If those within a specific licensed occupation are restricted from entering the higher-paying groups (e.g., physician specialists), they may “bump-

[8] As occupational licensing laws should not directly affect social programs or direct transfers, we conceptualize income as pre-tax, pre-redistribution income (“market income”; Franko, 2021; Hayes & Vidal, 2015).

down" into the lower paying groups (e.g., general practitioners) with the supply influx lowering pay even further in those groups" (p. 341). Yet, as mentioned above, such effects would be difficult to discern between occupations. Simply, high-wage occupations have more licensing saturation than other job types going back further in time (Lindsey & Teles, 2017). Since our data on wages and state income distributions are more recent, existing across-occupation differences would not be able to account for the within-occupation effects we estimate.

What is especially unclear from previous research is whether licensing in different types of occupations (high-wage, medium-wage, low-wage, for example) generate the differential wage rents that could affect state income distributions downstream. Thus, we are ultimately agnostic regarding which research hypothesis to hold until we estimate within-occupation wage premiums for the different occupation classes. In the next section, we do just that and estimate the extent of wage premiums within state-occupation code combinations as a function of increasing licensing over time. Such analysis allows us to test the conditional clause of the above hypotheses regarding wage premiums and where they are situated.

STATE LICENSING COVERAGE AND WITHIN-OCCUPATION WAGES

The goal of this section is to empirically assess the extent to which licensing affects wages at different points along state-occupational wage distributions. Previewing the main finding, we discover that the wage premiums that result from new licensing laws are larger for low- and medium-wage occupations than they are for high-wage occupations. We take this empirical finding as justification for adopting the *Decreasing Inequality Hypothesis* to motivate the "State Licensing Coverage and Income Inequality" section below.

In the current section, we build on existing research to examine the wage premium question in a very specific way. First, we study only *within-occupation* changes, estimating fixed effects models at the level of Bureau of Labor Statistics Standard Occupation Classification (SOC) 2010 6-digit codes.[9] Second, we identify licensed occupations using a novel dataset of state licensing regulations (Redbird, 2017, 2016), and measure licensing requirements dichotomously, as well more continuously with the (logged) number of workers covered by licensing requirements within occupational classifications.[10] Ultimately, we contribute to the literature on wage premiums by examining the extent to which occupational heterogeneity conditions the extent and placement of such premiums within occupational wage distributions.

Data and empirical strategy

We collect wage and licensing data from a variety of sources and organize them at the SOC 2010 code level across the period 2000 to 2016.[11] The wage data come from the BLS Occupational Employment

[9] https://www.bls.gov/soc/2010/

[10] There is of course a difference between licensing "coverage" at the level of an occupation or particular job role and an individual's "attainment" of a license to fill that role (Deyo et al., 2018). Economists tend to be rightly concerned with measuring attainment to control for individual skill-based factors that determine wages. They determine attainment mainly through survey instruments of workers (Gittleman et al., 2018; Kleiner & Krueger, 2010). Our goal though is more at the level of public policy and thus we are primarily interested in the effects changes in regulatory policy have on wages and, ultimately, income distributions—hence, we focus on coverage by law. We calculated coverage by law at the SOC 2010 6-digit level with Redbird's (2017) "coverage rate" as described here: "the BLS keeps data on the number of people in each Census occupation that fall into each SOC category. Using this comparison data, I constructed a coverage rate, based on the percent of each Census occupation that falls into licensed SOC occupations" (p. 609). Measuring coverage rather than attainment also allows us to estimate any residual effects of licensing spillovers (though these are impossible to disentangle from mechanical effects in our approach).

[11] We focus on this time period because SOC codes were not used by the BLS until 1999. The following description comes from https://www.bls.gov/soc/: "The Standard Occupational Classification (SOC) system is a federal statistical standard used by federal agencies to classify workers into occupational categories for the purpose of collecting, calculating, or disseminating data. All workers are classified into one of 867 detailed

and Wage Statistics (OEWS) program.[12] Yearly tables include information on wages (hourly and annual) and employment for each SOC occupation in each state. BLS reports nominal wage data in tables, so we deflate these figures to real values, but do so in a way that accounts for regional variation in cost of living. Thus, we use state-year level regional price parities (RPP) to modify each yearly price index. This implicit regional price deflator corrects for state-by-state heterogeneity and temporal inflation in wages.

To assess occupational class heterogeneity, we further categorize each occupation code as being either high-wage, medium-wage, or low-wage. While it is straightforward to conceptualize these different wage classes, we must be careful to measure them in a way that is not endogenous to the wage premiums they create.[13] We thus measure the mean regionally-deflated real wage for each 6-digit SOC 2010 code (across all years) and then compared each mean wage to the unweighted distribution of all such mean wages, designating those above the 75th percentile for all occupations to be high-wage, below the 25th percentile to be low-wage, and those between these two quantiles to be medium-wage.[14]

As an alternative to this strategy, we also categorize occupations by the skills that they require. The idea is that these skills are more likely to be exogenous to licensing changes than are wage classifications. Appendix B details how we used information from the O*NET database[15] to categorize 6-digit SOC codes as "high-skill," "medium-skill," or "low-skill" based on principal factor analysis of reported task-skill mixes (per Kleiner and Xu, in press, and Lise and Postel-Vinay, 2020). These skill categories are correlated with the wage classifications that we use in the main text Table 1 (χ^2 test, $p <$ 0.001; Cramer's V $\approx$ .32) and the results from Appendix Table B1 confirm that the results (more fully described below) are consistent between the two classification strategies.

There are a total of 867 distinct occupation codes across the states in these data. To account for unobserved heterogeneity across states, we further categorize each occupation-state pair as being a distinct occupational classification, yielding 42,178 distinct groups to study over time (some SOC codes do not exist within some states, so this is not quite 867 × 50). Appendix Table A1 gives a sense of the level of detail in SOC occupational granularity, while also displaying the 10 highest and lowest wage occupations in the data.

In order to assess whether licensing within an occupation-state pair affects wages, we need reliable over-time information on licensing regulations in the states. Previous research has relied on survey data with self-reported licensing requirements to measure the presence of regulation (Gittleman et al., 2018; Kleiner & Krueger, 2010). As an alternative to this, Redbird (2016, 2017) has developed an impressive dataset on licensing laws and regulations in the states.[16] We use these data to measure for

occupations according to their occupational definition. To facilitate classification, detailed occupations are combined to form 459 broad occupations, 98 minor groups, and 23 major groups. Detailed occupations in the SOC with similar job duties, and in some cases skills, education, and/or training, are grouped together." As we discuss in more detail below, the SOC codes are needed to match licensure requirements to the wage data by occupation, state, and year. We use SOC 2010 codes at the 6-digit level ("detailed occupations") of aggregation throughout.

[12] https://stats.bls.gov/oes/

[13] For instance, if wage premiums are large enough and we measure the wage classes by state-year, certain occupations can move in and out of wage classifications over time, perhaps as a direct result of their being newly licensed. We thank two anonymous reviewers for clearly articulating this point.

[14] This strategy works especially well for the low-wage and high-wage categories, but 33% of the time, an occupation that we categorize as medium-wage has earnings above the state-year median. Thus, as an alternative, we demonstrate in Appendix Table B2 that if we instead split the wage distribution at the across-state median, the largest wage premiums exist for those occupations below the median. This is consistent with what we find in the main text and when we alternatively classify jobs by skills in Table Appendix B1. All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's website and use the search engine to locate the article at http://onlinelibrary.wiley.com.

[15] https://www.onetcenter.org/database.html

[16] https://www.bethredbird.com/want-the-data/: "Licensing data is derived from an extensive coding of occupational legislation and regulations, enacted federally and across all 50 states from 1970 to 2017, and across all occupations classified by the Bureau of Labor Statistics Standard Occupational Classification system (SOC). During this time period, thousands of licensing laws were passed."

TABLE 1 The effect of occupational licensing on logged mean real wages (annual) by SOC classification, 2000 to 2016.

	1	2	3	4
Licensed profession	0.00859***	0.01559***		
	(0.00243)	(0.00468)		
Licensed profession × medium wage		−0.00039		
		(0.00595)		
Licensed profession × high wage		−0.02167***		
		(0.00614)		
Log # licensed workers in occupation			0.00069***	0.00082*
			(0.00017)	(0.00033)
Log # licensed workers × medium wage				0.00034
				(0.00042)
Log # licensed workers × high wage				−0.00095*
				(0.00044)
Year	0.00217***	0.00215***	0.00216***	0.00214***
	(0.00018)	(0.00018)	(0.00018)	(0.00018)
N	654467	654467	625217	625217
State-occupation code fixed effects	yes	yes	yes	yes

Notes: ***$p < 0.001$; **$p < 0.01$; *$p < 0.05$. Wage Type component terms excluded because they are collinear with state-occupation code fixed effects.

each state-SOC code pairing in each year 1) whether licensing was required for an occupation in that pairing and 2) the number of workers in such license-mandated occupations.

As mentioned, our preferred empirical specification is to group the data by state-SOC code pairing and calculate estimates of within-pairing changes in licensing on wages. Our main outcome variable is logged mean real wages at the annual level, though we also estimate quantile regressions using logged 10th, 25th, 50th, 75th, and 90th percentile real wages as outcomes. We model time in our 2000 to 2016 panels in two separate ways. First, the main tables show one-way way fixed effects with a discrete counter for the year of observation included as a regressor. We alternatively estimate two-way fixed effects models in Appendix Tables B4 and B6. These models are always consistent with the one-way fixed effects approach, which we ultimately prefer to the two-way fixed effects models, as two-way fixed effects can be quite difficult to identify and interpret properly (Kropko & Kubinec, 2020).

In addition to separately assessing the effects of a dichotomous licensing indicator and a continuous measure of licensing coverage, we also separately estimate aggregated effects of licensing and effects conditional on the type of occupation class (high-wage, medium-wage, and low-wage).

Mathematically, the empirical specification for the wage class differentiated models below can be expressed as

$$\begin{aligned}\ln\left(\text{Real State-Adjusted Mean Wage}_{it}\right) = \alpha_i + \beta_1(\text{Licensing Variable})_{it} + \beta_2\,(\text{Licensing Variable}_{it}\\ \times \text{Medium Wage Occupation}_i) + \beta_3\,(\text{Licensing Variable}_{it}\\ \times \text{High Wage Occupation}_i) + \delta\text{Year}_t + \text{u}_{it} \qquad (1)\end{aligned}$$

where i indexes for state*SOC occupation code combination, t indexes for year, and α_i are state*SOC occupation code fixed effects.

Analysis

Table 1 presents our main estimates of the effects of licensing on within-occupation wages from 2000 through 2016.[17] Column 1 gives the aggregated effect of the dichotomous licensing measure on mean wages. In this case, the introduction of licensing raises wages by about 0.9%. The *Year* term indicates that logged mean wages increase each year with the SOC occupations: the substantive effect here is about 0.2% of mean wage increases (accounting for inflation using real state-adjusted wages as described above) per year.

Column 3 of Table 1 confirms that licensing coverage in terms of logged workers who need a license in each SOC occupation also increases wages. This effect is statistically distinguishable from zero but is ultimately substantively small. A 1% increase in licensed workers within an occupational class is associated with about a .001% increase in wages.

Columns 2 and 4 of Table 1 begin to assess the extent to which there are heterogeneous effects by wage type. As noted above, we categorized each SOC code as being high-wage, medium-wage, or low-wage. The models reported in Table 1 (columns 2 and 4) include multiplicative interaction terms between the wage type indicators and the respective licensing measure, be it dichotomous licensing or continuous logged licensed workforce.[18] Thus, the component "Licensed Profession" and "Log # Licensed Workers in Occupation" terms give the effects of licensing on wages for low-wage occupations, and the interaction terms show how much the effect varies for the medium- and high-wage occupational classes.

Though it is clear from the table that there are wage premiums for low-wage occupations, we need to calculate standard errors for the marginal effects from the interactions of licensing with the other wage classes (Brambor et al., 2006). Thus, Figure 1 makes clear these marginal effects for each wage class. The persistent finding here is that wage premiums are significantly larger for medium-wage and low-wage occupations than they are for high-wage occupations. In fact, high-wage occupations see no positive wage premiums on average as a result of licensing. In particular, for the dichotomous licensing measure (left panel of Figure 1), the wage premium for medium-wage and low-wage occupations ranges from 1.1% to 1.9% while high-wage occupations actually experience statistically significant wage *discounts*. For the continuous licensing measure (right panel of Figure 1), there is no effect of increasing licensing on wages in the high-wage classification, but both premiums still exist for both the medium- and low-wage categorizations.[19]

It seems from this analysis that we should be adopting some form of the *Decreasing Inequality Hypothesis*, but need to first show that licensing has indeed been increasing in the medium- and/or low-wage classes that produce the largest average wage premiums. Recall that the logic of this hypothesis requires licensing to move the lower parts of the income distribution towards the top (through wage premiums in this case). A necessary condition for this kind of distributional shift is that there are greater wage premium for medium- and low-wage jobs than for high-wage occupations (this is satisfied by the above analysis) and that licensing over time is targeting these occupations in medium- and low-wage occupations. If these types of occupations are increasingly regulated, then the

[17] Appendix Table B4 presents analogous two-way fixed effects models and Appendix Table B3 presents an alternative specification which weights observations by the number of employees in the state-SOC classification pair in a given year, and Appendix Table B1 alternatively classifies occupations by requisite skill rather than wage category.

[18] The wage type component terms are excluded because they are collinear with the state-occupation code fixed effects.

[19] Previous research has not tested for heterogeneity in wage premiums by wage class, but it has assessed whether licensing affects differing quantiles of occupational wage distributions (Kleiner & Vorotnikov, 2017; Zhang & Gunderson, 2020). We do the same in Appendix B and show that both dichotomous and continuous licensing unconditionally affect each measured wage quantile. We also estimate these regressions conditional on wage class, as we do in the main text, which verifies that wage premiums are primarily reflected in median wages, though we are cautious about the quantile regressions because the BLS tables that we use to measure occupational wages have a good deal of missing data for non-median quantiles (see the varied *N* of the models in Appendix Tables B5 and B6). To confirm that the finding regarding median wages is not driven by the more expansive data, we also estimate the Q50 models from Appendix Tables B5 and B6 using only observations where BLS also reports Q10 wages. The inferences about licensing affecting median wages is supported here, with $\beta = 0.01589(0.00234)$ for a re-estimated Appendix Table B5 (top panel) and $\beta = 0.01587(0.00234)$ for a re-estimated Appendix Table B6 (top panel).

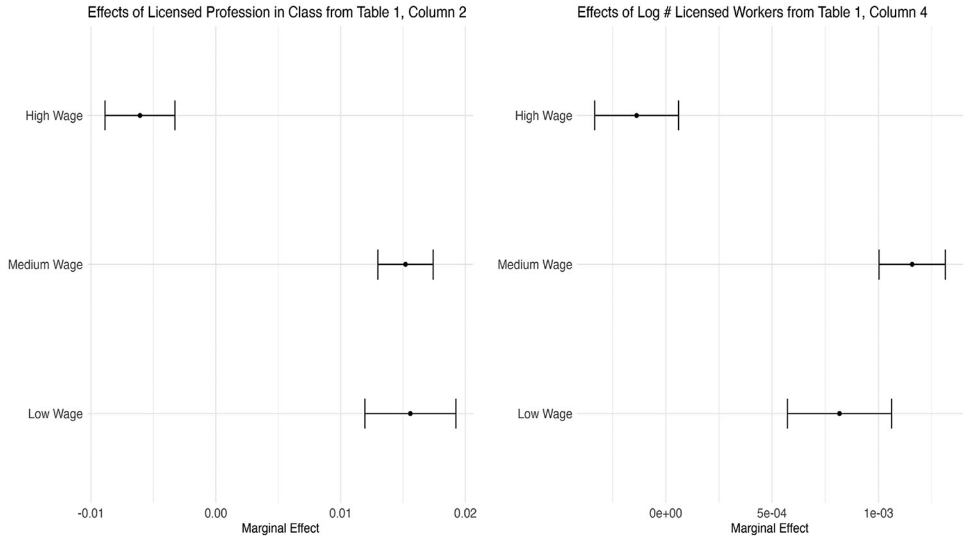

FIGURE 1 Marginal effects of licensing laws and coverage on logged mean real wages.

Notes: Marginal effects calculated from State-Occupation Code Fixed Effects models reported in columns 2 and 4 of Table 1. The Low Wage effects are given by $\hat{\beta}_{LicensingVariable}$, standard errors are $\sqrt{var(\hat{\beta}_{LicensingVariable})}$. For other wage classes, the effects are $\hat{\beta}_{LicensingVariable} + \hat{\beta}_{LicensingVariable \times Wage\ Type}$, with standard errors of $\sqrt{var(\hat{\beta}_{LicensingVariable}) + var(\hat{\beta}_{LicensingVariable \times WageType}) + 2 \times cov(\hat{\beta}_{LicensingVariable}, \hat{\beta}_{LicensingVariable \times WageType}}$

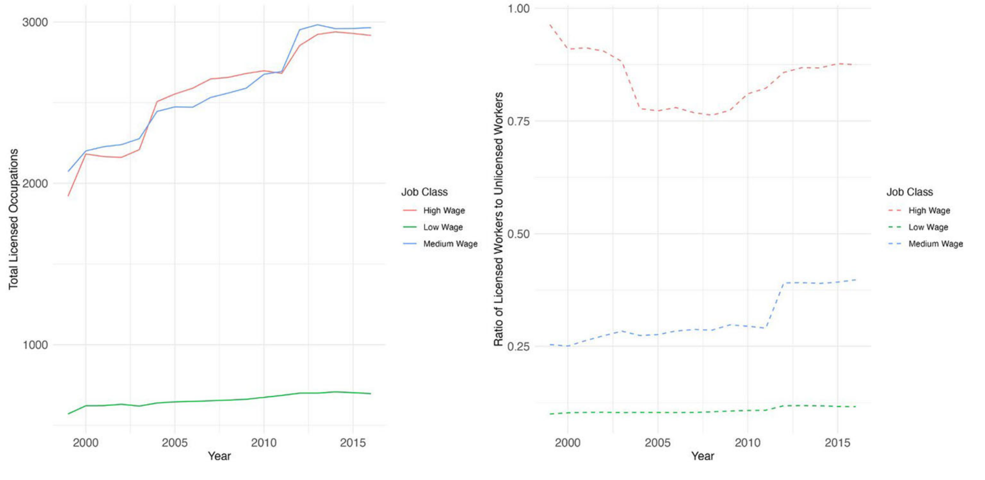

FIGURE 2 Licensing laws and occupational coverage, by job class.
[Color figure can be viewed at wileyonlinelibrary.com]
Notes: Data on licensing laws from Redbird (2017, 2016). Licensed workers calculated by matching licensing data at the SOC 2010 6-digit level to BLS data on total employees within occupation.

wage premiums they provide can draw lower wage workers up toward the upper ends of the income distribution.

Figure 2 demonstrates the degree of licensing regulation that exists in each wage class we have been discussing. The left panel of the figure shows the total number of licensed occupations (across all states) in each wage class, and the right shows the ratio of the total licensed workforce to the unlicensed workforce (again, across all states) in each class. This panel clearly shows that while licensing

TABLE 2 The effect of occupational licensing on logged total employment (annual) by SOC classification, 2000–2016.

	1	2
Licensed profession	−0.07351***	−0.09614***
	(0.00483)	(0.01678)
Licensed profession × medium wage		0.05153**
		(0.01829)
Licensed profession × high wage		0.00299
		(0.01801)
Year	0.00073**	0.00073**
	(0.00024)	(0.00024)
N	632378	631992
State-occupation code fixed effects	yes	yes

Note: ***$p < 0.001$; **$p < 0.01$; *$p < 0.05$

regulations are relatively rare for low-wage jobs, they are increasingly common for medium- and high-wage occupations. The right panel of Figure 2 shows the more meaningful ratio of licensed to unlicensed workers in each wage-based job class. We see here that there is variation in such licensing coverage across the high- and medium-wage categories. We mentioned above that high-wage occupations may already have been saturated in licensing regulations going back decades. The right panel of Figure 2 confirms this, with nearly as many licensed as unlicensed high-wage workers (ratio near 1) at the beginning of our time series. This ratio actually declines for a period until it recovers a bit post-2011 (but levels off below its year 2000 peak). On the other hand, the ratio of licensed to unlicensed workforce in medium-wage occupations increases steadily over our time period, until it experienced a significant bump between 2011 and 2012. Increases in licensing coverage are more muted for low-wage occupations.[20]

According to the *Decreasing Inequality Hypothesis*, this growth in medium-wage licensing should be especially consequential for state income distributions, considering that we have now demonstrated that wage premiums exist in this occupation class and that there is an identifiable growth in occupational licensing for these types of occupations. We expect that licensed medium-wage workers will move up the wage distribution beyond medium-wage non-licensed workers and move toward those in the higher-wage occupations. We hypothesize that the net effect of such wage shifting should compress the overall income distribution when licensing increases within states. Using detailed data on occupational wages and a comprehensive source of licensing by occupational classification, we have found wage premium effects that point us toward the *Decreasing Inequality Hypothesis*, yet there is an important caveat to consider before we test this hypothesis in the next section. As reviewed above, the effects of licensing can be complicated and economic theory suggests that wage premiums are driven in part by the reduction of labor supply that licensing brings (Kleiner, 2000; Samuelson & Nordhaus, 2009). Thus, it is likely the case that increased licensing regulations affect total employment within occupational categories. If it is the case that licensing brings wage premiums *and* decreased employment in licensed occupations, the two effects could cancel out in the aggregate.

Table 2 confirms that licensing does reduce employment within an occupation after it is adopted, but that the effects are substantively small. According to column 1, upon the introduction of licensing within a SOC code, employment decreases by about 0.07%. Column 2 and Figure 3 further demon-

[20] Changes in licensing coverage can be driven by increases in licensing regulations (reflected in the left panel of Figure 2) or by growth in occupations where licensing is more prevalent. To decompose these possible determinants of licensing coverage, we simply regress the yearly ratio of licensed to unlicensed workers on the overall number of licensed occupations. This bivariate regression explains about 46% of the variance in the ratio measure, leaving 54% presumably explained by growth in licensed occupations outpacing that for unlicensed occupations.

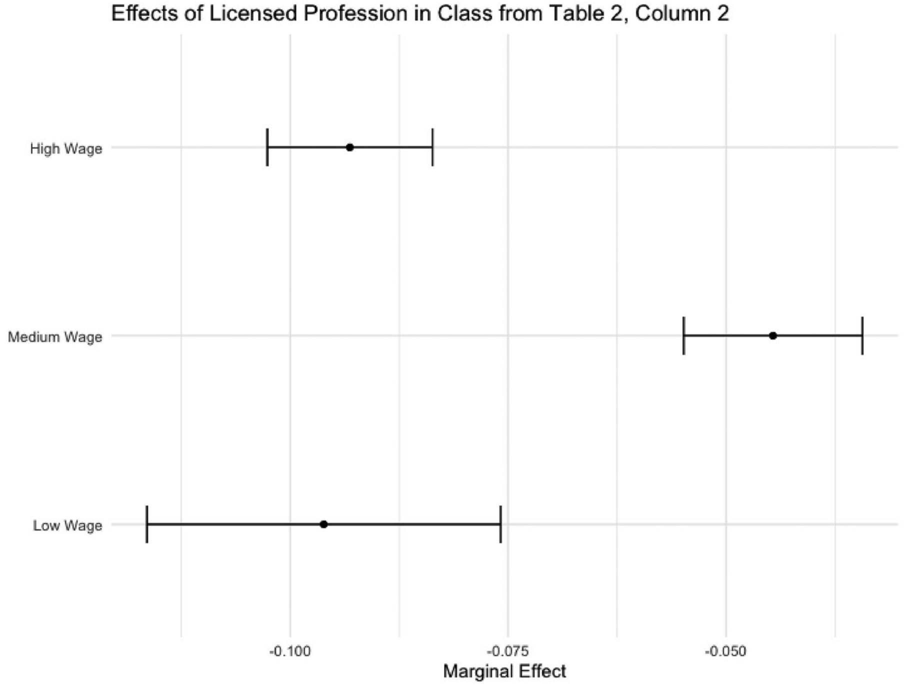

FIGURE 3 Marginal effects of licensing laws on logged total employment.

Notes: Marginal effects calculated from State-Occupation Code Fixed Effects models reported in columns 2 of Table 2. The Low Wage effects are given by $\hat{\beta}_{LicensingVariable}$, standard errors are $\sqrt{var(\hat{\beta}_{LicensingVariable})}$. For other wage classes, the effects are $\hat{\beta}_{LicensingVariable} + \hat{\beta}_{LicensingVariable \times Wage\ Type}$, with standard errors of $\sqrt{var(\hat{\beta}_{LicensingVariable}) + var(\hat{\beta}_{LicensingVariable \times WageType}) + 2 \times cov(\hat{\beta}_{LicensingVariable}, \hat{\beta}_{LicensingVariable \times WageType}}$

strate that although there are reductions in employment for each wage classification, the reductions are statistically the smallest for medium-wage occupations (they are about half the size as the reductions for high- and low-wage licensing). Thus, while it is possible that such reductions in employment can reduce the income gains from wage premiums (Table 1), it is also possible that the effects of the wage premiums and the increasing proportion of the medium-wage workforce that is licensed (Figure 2) can still serve to compress state income distributions. Evaluating these differing possibilities is the task of the following section.

STATE LICENSING COVERAGE AND INCOME INEQUALITY

Since it is the case that wage premiums are larger for medium- and low-wage occupations and licensing has increased most in recent years in those occupation types, it stands to reason that licensing increases the wage resources of those who would otherwise be lower in state distributions. Given the connection between wages and annual income, we now turn to testing the *Decreasing Inequality Hypothesis* stipulated above. Essentially, we expect that when licensing regulations become more prevalent in a state, common measures of income inequality should move toward less unequal distributions within the state.

Data and empirical strategy

In this section, we move from occupation codes as the primary units of analysis to U.S. states. Similar to above though, we seek primarily to leverage within-state changes in licensing to explain variation in state-level inequality, using a variety of aggregate measures. As above, the year coverage in our data for this section is the 2000 to 2016 period.

Following previous research (Franko, 2021), the primary dependent variable here is the ratio of the income share of those in the 80th percentile and above of state income distributions and those below the 20th percentile. This measure is calculated using household data from the Census Bureau's Current Population Survey Annual Social and Economic Supplement (CPS-ASEC).[21] We favor this inequality ratio over alternatives for a number of reasons. To start, it provides a straightforward and easily understood interpretation: the ratio value directly illustrates the extent to which the affluent out-earn the less affluent within a particular state and year. To illustrate, a ratio of 5 (the approximate mean ratio in our data) means that those in the upper 20% of a state-year income distribution earn five times more than those in the lower 20%. Next, the measure utilizes information from both the bottom and top of state income distributions, which should be differentially affected by the various wage premiums from different wage classes as we found above. Crucially, we can assess the implications of these wage premiums by modeling the top 20% share and bottom 20% share separately, in addition to the ratio of the two. And as the expansion of inequality over the last several decades appears to be largely driven by the rising incomes of the rich at the expense of those in bottom portion of the income distribution (Piketty & Saez, 2003), it is essential that the measure of inequality being used can capture these changes. One advantage of using the inequality ratio described here is that it accounts for these attributes of inequality while other measures do not. The widely used Gini coefficient, for instance, does a particularly poor job of detecting changes at the top and bottom of the income distribution (see Atkinson, 1970).

Appendix Figure A2 demonstrates the variation that exists in the measure of state income distributions in our data (and Figure A3 does the same for the 10% alternative dependent variable). The plot shows that the ratio measure varies substantially, both between states and within states over time. For example, while income inequality in New Mexico and Tennessee are similar on average, over-time changes within New Mexico are much larger than those observed in Tennessee. For another comparison, consider Mississippi and Iowa. Mississippi has a high level of inequality on average and large variations in the ratio over time, while Iowa has relatively less over-time variation and is near the bottom of the list in terms of average inequality. Many other comparisons can be made, but the main point is that the observed variations in state inequality leave open the possibility that state licensing laws may be one factor that contributes to these differences in income distributions.

As in the section "State Licensing Coverage and Within-Occupation Wages," we turn to the Redbird (2016, 2017) data to measure the extent to which state policy regulates labor markets by licensing occupations. As described above, the dataset is a census of licensing statutes in each state and is organized at the license-occupation unit. That is, some regulations affect multiple occupations within states and the data are disaggregated to occupation-license pairs. This level of granularity is not necessary for our purposes, though, as we lack full income distribution data per occupation. Thus, we aggregate licensing laws up to the level of the state-year, based on the year each licensing regulation took effect. As detailed as these data are, we must ignore heterogeneity in the regulatory burdens that licenses

[21] Data were accessed at IPUMS (https://cps.ipums.org/cps/). We use standard adjustments for household size (by dividing total household income by the square root of number of people in the household) and inflation (using the CPI). The income shares are pre-redistribution, meaning the calculations do not include direct government transfers. We also consider alternative income share measures that exclude several sources of income that are arguably unlikely to be directly or indirectly shaped by licensing regulations. Finally, we also use top 10%, bottom 10%, and the ratio between these as dependent variables. The results of these models, along with additional details about the measures of inequality we use, can be found in Appendix C.

demand on potential workers. Although there can be quite a bit of such variation,[22] we use the total licensed worker coverage in a state as a proxy for the overall regulation of the state labor market that we hypothesize will affect aggregate income distributions. Coverage is calculated by merging the licensing data with the BLS occupational data as described in Section 3 and then summing the total workers in these occupations and the total workforce in the state in each year. Since the total size of state workforces (licensed and unlicensed) changes over time, we normalize the licensed coverage by ultimately calculating the *Proportion of Workforce Licensed* by dividing the number of workers covered by licensing laws by the total state workforce in each state-year (as we do with all of the proportion/percentage covariates, we multiply this value by 100 for ease of interpretation).

In addition to this main licensing coverage variable, we also include several other measures of state characteristics that are likely to influence a state's income distribution. We do not have strong theoretical expectations for these variables and include them primarily to control for time-varying state-level heterogeneity that may affect state income distributions and be correlated with licensing over time. These variables include two measures of state government power. The first accounts for the ideological composition of the state legislature (*Gov. Ideology*) and the second measures partisan control of both legislative chambers and the party affiliation of the governor (*Gov. Party Control*). Higher values on the former measure indicate that the state government is more liberal and higher values on the latter measure indicates stronger Democratic Party control over state government. We also include variables that capture the percentage of union members in each state (*Union Mem.*), per capita *Real GDP*, percentage of the population that is non-Hispanic White (*Pct. White*), and percentage of the population that is 60 years of age or older (*Pct. over Age 60*).[23]

In the main text, we estimate the determinants of within-state measures of income inequality controlling for state fixed effects, a yearly trend, and the time varying controls specified above. In Appendix C, we demonstrate that our main results are robust to alternatively estimating error correction models, which are common in studies of studies of income inequality (for recent examples, see Franko, 2016; Franko & Witko, 2017; Witko, 2016).[24]

Mathematically, the empirical specification for the state inequality models below can be expressed as

$$\text{Inequality Ratio}_{it} = \alpha_i + \beta(\text{Proportion of Workforce Licensed})_{it} + \psi\,(X_{it}) + \delta\text{Year}_t + u_{it}$$

where i indexes for state, t indexes for year, X_{it} is a matrix of state-level controls, and α_i are state fixed effects.

[22] For example, potential makeup artists in Alaska must pay a $450 fee, complete 350 hours of training, and take two exams; while the only requirement in Nebraska is a $10 fee. Further, 10 states do not require a license for this profession at all and others require smaller fees than Alaska, but far more training (Georgia, Kansas, Kentucky, and Alabama each require 1,000 hours of training to obtain a license; https://ij.org/report/license-work-2/ltw2-data/. The multiple dimensions and extent of variation in these burdens makes it difficult to operationalize the restrictiveness of individual licensing laws).

[23] The government ideology measure is from Berry et al. (2013). Government party control is an additive index created from three separate indicator variables: party majority the lower chamber, party majority in the upper chamber, and party affiliation of the governor. Each indicator takes on a value of 1 for a Democratic legislative majority or Democratic governor, a value of −1 for a Republican legislative majority or Republican governor, and a value of 0 if the chamber is split or if the governor is not affiliated with one of the two major parties. These indicators are then added together, resulting in a measure that ranges from −3 for complete Republican control of all three institutions to +3 for complete Democratic control. Union membership data is from http://unionstats.com/ (Hirsch & MacPherson, 2003). The measures of per capita GDP, race, and age are all from the U.S. Census.

[24] ECMs also allow for the simultaneous estimation of both the short-term (or contemporaneous) effects and long-term effects of each independent variable on the dependent variable (De Boef & Keele, 2008; Enns et al., 2014). Appendix Table C3 presents results of three ECMs, one for each inequality outcome. Here, the coefficients on the differenced variables (Δ) gives the short-run effects on inequality and the lagged variables (t−1) gives the long-run effects. Appendix Table C4 presents total effects for the statistically impactful licensing, union, and GDP variables. Overall, the ECMs confirm that our *Proportion of Workforce Licensed* variable has short-run effects on the ratio of Top 20% to Bottom 20% incomes, which can be attributed to long-run reductions in Top 20% incomes and short-run increases in Bottom 20% incomes.

TABLE 3 The effect of occupational licensing coverage on top and bottom income shares, 2000 to 2016, state fixed effects models.

	Top 20% / Bottom 20% ratio	Top 20% income	Bottom 20% income
Proportion of workforce licensed	−0.02706*	−0.03137*	0.00663*
	(0.01073)	(0.01482)	(0.00267)
Gov. ideology	−0.00499	−0.00177	0.00032
	(0.00634)	(0.00876)	(0.00158)
Gov. party control	−0.00776	−0.07736	0.00510
	(0.07281)	(0.10059)	(0.01813)
Union mem.	−0.12676*	−0.19761**	0.02369
	(0.05230)	(0.07226)	(0.01302)
Real GDP (per cap.)	−0.00569	0.00600	−0.00122
	(0.01535)	(0.02120)	(0.00382)
Pct. White	−0.05331	−0.14090	0.00176
	(0.06661)	(0.09203)	(0.01659)
Pct. over age 60	0.32568**	0.51832***	−0.05397*
	(0.10732)	(0.14827)	(0.02672)
Year	−0.02850	−0.23081***	−0.01429
	(0.04060)	(0.05609)	(0.01011)
N	800	800	800
State Fixed Effects	yes	yes	yes
R^2	0.07479	0.07551	0.13295
Adj. R^2	0.00371	0.00449	0.06635
Num. obs.	800	800	800

Note:$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Analysis

Table 3 presents the results from three regression models, each estimating the influence of licensing on different measures of state income inequality. The first column reports determinants of the ratio between the Top 20% income share and the Bottom 20% income share, while the second and third columns disaggregate effects for the Top 20% and Bottom 20% income shares, respectively.

The primary empirical support for the *Decreasing Inequality Hypothesis* comes from the effect of the *Proportion of Workforce Licensed* term on the Top 20%/Bottom 20% ratio found in column 1 of Table 3. Although the substantive impact is quite small, this effect is distinguishable from zero as a mitigator of state income inequality. A 1% increase year-on-year in the proportion covered by licensing laws reduces the Top 20%/Bottom 20% ratio by .027. Compared to the effect of unionization, this is quite small, but these factors (licensing and union membership) are the only two significant non-demographic determinants of income inequality in this specification. To compare, a 1% increase year-on-year in union membership reduces the inequality ratio by .127, which is nearly 5 times larger than the effect of licensing. This effect is consistent with the findings from the literature on union membership and economic inequality (Ahlquist, 2017; Card et al., 2017).

What drives the correlation between these two policy choices (licensing regulation and policies affecting union membership) and aggregate inequality, as measured by the Top/Bottom ratio? Columns 2 and 3 of Table 3 allow us to separately assess the extent to which each affects Top 20% income shares (column 2) and Bottom 20% income shares (column 3). We see that both licensing and unionization serve to significantly reduce Top 20% income shares. While a 1% increase in unionization reduces the top income shares by .197, a 1% increase in the proportion of the workforce licensed decreases this share by just .03. Since the Top 20% income share ranges from 36.28 to 59.67, these are both modest substantive decreases, though both are statistically discernible from zero. On the other hand, only increases in licensing actually increase the Bottom 20% income shares, by .006 for each 1% increase.

These increases in Bottom 20% income shares are most clearly associated with the mechanisms under-girding the *Decreasing Inequality Hypothesis* from Section 2. Since the wage premiums (established in the "State Licensing Coverage and Within-Occupation Wages" section) from licensing are concentrated in low- and medium-wage (and skills, per Appendix Table B1) occupations, licensing can increase the Bottom 20% income shares when licensing becomes more prevalent within a state. However, the same mechanism can also increase income shares nearer to the center of state income distributions (quantile regressions in Appendix B confirm that licensing primarily affects median wages, as opposed to only the top of occupation-specific wage distributions), which would serve to compress the overall distribution and reduce the Top 20% income shares from column 2.

DISCUSSION/CONCLUSION

In this paper, we have sought to discern the connection between occupational licensing regulations and income inequality in the U.S. states. We build an argument that follows from previous findings regarding the wage premiums that many licensing laws have been found to create. Yet, we add nuance to this literature and show that the extent of wage premiums depends on the wage class of the occupation. In particular, since medium- and low-wage jobs seem to garner larger wage premiums than high-wage occupations and given that recent increases in licensing laws have concentrated on non-high-wage occupations, we develop and adopt a *Decreasing Inequality Hypothesis*.

Since licensing is largely a state policy decision, we examined our hypothesis in the context of a state-year panel of licensing laws and characteristics of state income distributions (focusing on top and bottom income shares). This approach allows us to track growing trends in occupational licensing and income inequality and control for confounders (such as government composition, union density, and economic growth) in estimating the extent to which changes in income inequality are correlated with labor market regulation. Our findings indicate consistent effects of licensing regulations on income inequality in the states. Contrary to the expectations of Lindsey and Teles (2017), we conclude that increases in licensing have actually served to mitigate further growth in income inequality in the states. State policy can ameliorate income disparities (Franko & Witko, 2017), even in unintended and indirect ways.

Our dependent variables are measured as features of entire state income distributions and are reasonably most sensitive to macroeconomic forces of growth and federal and state fiscal and redistributive policies. We control for these factors and still find that market conditioning through occupational licensing laws dynamically affects state income inequality in distinguishable ways. In fact, our findings likely represent a lower bound on the effects of occupational licensing regulations on income inequality.

In particular, our independent and dependent variables are currently measured rather coarsely. The NLD database (Redbird, 2016) is a major improvement on cross-sectional comparisons of licensing regulations in the states and on longitudinal studies of particular types of occupations (see Redbird, 2017, for a comprehensive review). Yet, as mentioned above, we abstract away from the details of state regulations, which can vary quite a bit in level of restrictiveness. In addition, our dependent variables are quite blunt and can be sharpened in future research, especially with an eye to testing more specific arguments. For example, we intend to create more tailored measures of state income inequality likely to be most affected by licensing laws. We could do this by creating industry-specific characterizations of income inequality within states and relate these measures to licensing requirements in these areas.

This research design would mimic that presented in Section 3 on wage premiums and can allow us to confirm the specific mechanism of our aggregate findings.

Finally, occupational licensing laws have been found to increase the prices of goods and services produced by those for whom a license is required (Kleiner et al., 2016). If this is the case, then these regulations can have an additional implication for economic inequality beyond what we find here. That is, increased prices for common goods would function as a regressive tax on the poor that would surely condition consumption and savings, and perhaps offset the results that show that licensing reduces income inequality. By examining consumption and savings for those at different quantiles of the income distribution, we can further isolate the implications of occupational licensing for state wealth inequality, in addition to income.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available at https://doi.org/10.7910/DVN/OACTQG.

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REFERENCES

Acemoglu, D., & Autor, D. (2011). Skills, tasks and technologies: Implications for employment and earnings. In O. Ashenfelter & D. Card (Eds.), *Handbook of labor economics* (Vol. 4, pp. 1043–1171). Elsevier.

Adolph, C., Breunig, C., & Koski, C. (2020). The political economy of budget tradeoffs. *Journal of Public Policy*, *40*(1), 25–50.

Ahlquist, J. S. (2017). Labor unions, political representation, and economic inequality. *Annual Review of Political Science*, *20*, 409–432. https://doi.org/10.1146/annurev-polisci-052615-025327

Atkinson, A. B. (1970). On the measurement of inequality. *Journal of Economic Theory*, *2*(3), 244–263. https://doi.org/10.1016/0022-0531(70)90039-6

Autor, D., Manning, A., & Smith, C. (2016). The contribution of the minimum wage to U.S. wage inequality over three decades: A reassessment. *American Economic Journal: Applied Economics*, *8*(1), 58–99. https://doi.org/10.1257/app.20140473

Autor, D. H., Katz, L. F., & Krueger, A. B. (1998). Computing inequality: Have computers changed the labor market? *The Quarterly Journal of Economics*, *113*(4), 1169–1213. https://doi.org/10.1162/003355398555874

Bartels, L. M. (2008). *Unequal democracy: The political economy of the new gilded age*. Princeton University Press.

Benham, L., & Benham, A. (1975). Regulating through the professions: A perspective on information control. *The Journal of Law and Economics*, *18*(2), 421–447. https://doi.org/10.1086/466817

Bergal, J. (2015, January). *A license to braid hair? Critics say state licensing rules have gone too far*. Pew Stateline.

Bergh, A., & Nilsson, T. (2010). Do liberalization and globalization increase income inequality? *European Journal of Political Economy*, *26*(4), 488–505.

Berry, W. D., Fording, R. C., Ringquist, E. J., Hanson, R. L., & Klarner, C. (2013). A new measure of state government ideology, and evidence that both the new measure and an old measure are valid. *State Politics & Policy Quarterly*, *13*(2), 164–182. https://doi.org/10.1177/1532440012464877

Brambor, T., Clark, W. R., & Golder, M. (2006). Understanding interaction models: Improving empirical analyses. *Political Analysis*, *14*(1), 63–82.

Card, D., & DiNardo, J. E. (2002). Skill-biased technological change and rising wage inequality: Some problems and puzzles. *Journal of Labor Economics*, *20*(4), 733–783.

Card, D., Lemieux, T., & Riddell, W. C. (2017). Unions and wage inequality. In *What do unions do?* (pp. 114–159). Routledge.

Carroll, S. L., & Gaston, R. J. (1981). Occupational restrictions and the quality of service received: Some evidence. *Southern Economic Journal*, *47*(4), 959–976. https://doi.org/10.2307/1058155

Cobb, A. (2016). How firms shape income inequality: Stakeholder power, executive decision making, and the structuring of employment relationships. *Academy of Management Review*, *41*(2), 324–348.

Council of Economic Advisers. (2020, February). *Economic report of the President*. The White House. https://www.whitehouse.gov/wp-content/uploads/2021/07/2020-ERP.pdf

Council of Economic Advisers. (2022, April). *Economic report of the President*. The White House. https://www.whitehouse.gov/wp-content/uploads/2022/04/ERP-2022.pdf

Cox, C., & Foster, S. (1990, October). *The costs and benefits of occupational regulation* [Technical report]. Federal Trade Commission, Bureau of Economics. https://www.ftc.gov/system/files/documents/reports/costs-benefits-occupational-regulation/cox_foster_-_occupational_licensing.pdf

De Boef, S., & Keele, L. (2008). Taking time seriously. *American Journal of Political Science*, *52*(1), 184–200. https://doi.org/10.1111/j.1540-5907.2007.00307.x

Deyo, D., Timmons, E., & Kleiner, M. (2018, November 27). *A response to "New closed shop: The economic and structural effects of occupational licensure"* [Policy brief]. George Washington University, Mercatus Center. https://www.mercatus.org/research/policy-briefs/response-new-closed-shop-economic-and-structural-effects-occupational

Dodini, S. (2023). The spillover effects of labor regulations on the structure of earnings and employment: Evidence from occupational licensing. *Journal of Public Economics*, *225*, 104947.

Enns, P. K., Kelly, N. J., Morgan, J., Volscho, T., & Witko, C. (2014). Conditional status quo bias and top income shares: How U.S. political institutions have benefited the rich. *Journal of Politics*, *76*(2), 289–303. https://doi.org/10.1017/S0022381613001321

Faricy, C. G. (2015). *Welfare for the wealthy: Parties, social spending, and inequality in the United States*. Cambridge University Press.

Feldman, R., & Begun, J. W. (1985). The welfare cost of quality changes due to professional regulation. *The Journal of Industrial Economics*, *34*(1), 17–32. https://doi.org/10.2307/2098479

Fortin, N., & Lemieux, T. (1997). Institutional changes and rising wage inequality: Is there a linkage? *Journal of Economic Perspectives*, *11*(2), 75–96.

Franko, W. W. (2016). Political context, government redistribution, and the public's response to growing economic inequality. *The Journal of Politics*, *78*(4), 957–973. https://doi.org/10.1086/686025

Franko, W. W. (2021). How state responses to economic crisis shape income inequality and financial well-being. *State Politics & Policy Quarterly*, *21*(1), 31–54.

Franko, W. W., Kelly, N. J., & Witko, C. (2016). Class bias in voter turnout, representation, and income inequality. *Perspectives on Politics*, *14*(2), 351–368. https://doi.org/10.1017/S1537592716000062

Franko, W. W., & Witko, C. (2017). *The new economic populism: How states respond to economic inequality*. Oxford University Press.

Gittleman, M., Klee, M. A., & Kleiner, M. M. (2018). Analyzing the labor market outcomes of occupational licensing. *Industrial Relations: A Journal of Economy and Society*, *57*(1), 57–100. https://doi.org/10.1111/irel.12200

Gittleman, M., & Kleiner, M. M. (2016). Wage effects of unionization and occupational licensing coverage in the United States. *ILR Review*, *69*(1), 142–172.

Hacker, J. S., & Pierson, P. (2010). *Winner-take-all politics: How Washington made the rich richer–and turned its back on the middle class*. Simon and Schuster.

Harrington, D. E., & Krynski, K. J. (2002). The effect of state funeral regulations on cremation rates: Testing for demand inducement in funeral markets. *The Journal of Law and Economics*, *45*(1), 199–225. https://doi.org/10.1086/324652

Harrington, D. E., & Treber, J. (2009, February). *Designed to exclude: How interior design insiders use government power to exclude minorities & burden consumers*. [Technical report]. Institute for Justice.

Hatch, M. E., & Rigby, E. (2015). Laboratories of (in)equality? Redistributive policy and income inequality in the American states. *Policy Studies Journal*, *43*(2), 163–187. https://doi.org/10.1111/psj.12094

Haupt, A. (2023). Who profits from occupational licensing? *American Sociological Review*, *88*(6), 1104–1130.

Hayes, T. J., & Vidal, D. X. M. (2015). Fiscal policy and economic inequality in the U.S. states: Taxing and spending from 1976 to 2006. *Political Research Quarterly*, *68*(2), 392–407. https://doi.org/10.1177/1065912915578461

Helpman, E. (2016). *Globalization and wage inequality* [Technical report]. National Bureau of Economic Research.

Hirsch, B. T., & MacPherson, D. A. (2003). Union membership and coverage database from the current population survey: Note. *Industrial & Labor Relations Review*, *56*(2), 349–354.

Jansa, J. M. (2020). Chasing disparity: Economic development incentives and income inequality in the U.S. states. *State Politics & Policy Quarterly*, *20*(4), 462–488. https://doi.org/10.1177/1532440019900259

Keller, E., & Kelly, N. J. (2015). Partisan politics, financial deregulation, and the new gilded age. *Political Research Quarterly*, *68*(3), 428–442. https://doi.org/10.1177/1065912915591218

Kelly, N. J. (2009). *The politics of income inequality in the United States*. Cambridge University Press.

Kelly, N. J. (2020). *America's inequality trap*. University of Chicago Press.

Kelly, N. J., & Witko, C. (2012). Federalism and American inequality. *Journal of Politics*, *74*(2), 414–426. https://doi.org/10.1017/S0022381611001678

Kim, C., & Sakamoto, A. (2008). The rise of intra-occupational wage inequality in the United States, 1983 to 2002. *American Sociological Review*, *73*(1), 129–157.

Kleiner, M. (2006). *Licensing occupations: Ensuring quality or restricting competition?* W.E. Upjohn Institute for Employment Research.

Kleiner, M., & Xu, M. (in press). Occupational licensing and labor market fluidity. *Journal of Labor Economics*.

Kleiner, M. M. (2000). Occupational licensing. *Journal of Economic Perspectives*, *14*(4), 189–202.

Kleiner, M. M., & Krueger, A. B. (2010). The prevalence and effects of occupational licensing. *British Journal of Industrial Relations*, *48*(4), 676–687. https://doi.org/10.1111/j.1467-8543.2010.00807.x

Kleiner, M. M., & Krueger, A. B. (2013). Analyzing the extent and influence of occupational licensing on the labor market. *Journal of Labor Economics*, *31*(S1), S173–S202. https://doi.org/10.1086/669060

Kleiner, M. M., Marier, A., Park, K. W., & Wing, C. (2016). Relaxing occupational licensing requirements: Analyzing wages and prices for a medical service. *The Journal of Law and Economics*, *59*(2), 261–291.

Kleiner, M. M., & Vorotnikov, E. (2017). Analyzing occupational licensing among the states. *Journal of Regulatory Economics*, *52*(2), 132–158. https://doi.org/10.1007/s11149-017-9333-y

Koumenta, M., & Pagliero, M. (2019). Occupational regulation in the European Union: Coverage and wage effects. *British Journal of Industrial Relations*, *57*(4), 818–849.

Kropko, J., & Kubinec, R. (2020). Interpretation and identification of within-unit and cross-sectional variation in panel data models. *PLOS ONE*, *15*(4), e0231349.

Langer, L. (2001). The consequences of state economic development strategies on income distribution in the American states, 1976 to 1994. *American Politics Research*, *29*(4), 392–415.

Leland, H. E. (1979). Quacks, lemons, and licensing: A theory of minimum quality standards. *Journal of Political Economy*, *87*(6), 1328–1346. https://doi.org/10.1086/260838

Lindsey, B., & Teles, S. M. (2017). *The captured economy: How the powerful enrich themselves, slow down growth, and increase inequality*. Oxford University Press.

Lise, J., & Postel-Vinay, F. (2020). Multidimensional skills, sorting, and human capital accumulation. *American Economic Review*, *110*(8), 2328–2376.

Meszaros, J. (2018). Inequality and unionization within the United States. *The Quarterly Review of Economics and Finance*, *67*, 326–333. https://doi.org/10.1016/j.qref.2017.07.013

National Conference of State Legislatures. (2020). *Occupational licensing final report: Assessing state policies and practices*. National Conference of State Legislatures. https://www.ncsl.org/labor-and-employment/occupational-licensing-final-report

Piketty, T., & Saez, E. (2003). Income inequality in the United States, 1913–1998. *Quarterly Journal of Economics*, *118*(1), 1–39.

Redbird, B. (2016). *Northwestern licensing database*. DOL/ETA: DOLJ111A21738. NSF: 1303612.

Redbird, B. (2017). The new closed shop? The economic and structural effects of occupational licensure. *American Sociological Review*, *82*(3), 600–624. https://doi.org/10.1177/0003122417706463

Samuelson, P. A., & Nordhaus, W. D. (2009). *Economics* (19th ed.). McGraw-Hill.

Shapiro, C. (1986). Investment, moral hazard, and occupational licensing. *The Review of Economic Studies*, *53*(5), 843–862. https://doi.org/10.2307/2297722

Shepard, L. (1978). Licensing restrictions and the cost of dental care. *The Journal of Law and Economics*, *21*(1), 187–201. https://doi.org/10.1086/466916

Smeeding, T. M. (2005). Public policy, economic inequality, and poverty: The United States in comparative perspective. *Social Science Quarterly*, *86*(s1), 955–983.

Volscho, T. W., & Kelly, N. J. (2012). The rise of the super-rich: Power resources, taxes, financial markets, and the dynamics of the top 1 percent, 1949 to 2008. *American Sociological Review*, *77*(5), 679–699. https://doi.org/10.1177/0003122412458508

Western, B., & Rosenfeld, J. (2011). Unions, norms, and the rise in U.S. wage inequality. *American Sociological Review*, *76*(4), 513–537.

White House. (2015). *Occupational licensing: A framework for policymakers*. Report prepared by the Department of the Treasury Office of Economic Policy, Council of Economic Advisors, and Department of Labor.

Witko, C. (2016). The politics of financialization in the United States, 1949–2005. *British Journal of Political Science*, *46*(2), 349–370. https://doi.org/10.1017/S0007123414000325

Witko, C., Morgan, J., Kelly, N. J., & Enns, P. K. (2021). *Hijacking the agenda: Economic power and political influence*. Russell Sage Foundation.

Zhang, T., & Gunderson, M. (2020). Impact of occupational licensing on wages and wage inequality: Canadian evidence 1998–2018. *Journal of Labor Research*, *41*, 338–351.

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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