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Occupational Licensing and Occupational Mobility

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Abstract:
This paper estimates the impact of occupational licensing at the extensive margin (existence) and intensive margin (qualifications) on the occupational mobility of US workers. Using 2015–2022 Current Population Survey data on worker occupational choices matched to licensing-policy data, I show that the existence of licensing regulation significantly reduces the probability that a worker enters an occupation. This reduced mobility is largely due to licensing fees and minimum thresholds for age and education. This finding may help explain the weak relationship between licensure and product market quality, as binding licensing qualifications likely have mixed links to worker skills.

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1 Introduction

In the last several decades, the United States has experienced sizable growth in occupational licensing, regulation requiring a credential based on select criteria and awarded by federal, state (typically), or local government that allows a worker to perform a job. While the occupational licensing rate was roughly 5 percent in the 1950s, 60 years later, approximately 29 percent of US workers were required to hold a license to perform their jobs (Kleiner and Krueger 2013). Advocates of occupational licensing argue that it reduces potential safety risks to consumers and improves the general quality of goods and services. However, opponents of occupational licensing claim that it creates an unnecessary barrier to entry for workers given mixed evidence about consumer benefits (Sweetland and Carpenter II 2022). They note that licensing may even reflect rent-seeking behavior for personal gain by some advocates. Since many licensing regulations vary at the state-occupation level, licensing policy that hinders mobility across geographies and occupations is of particular concern, and some existing research finds evidence of such negative mobility effects (for example, Johnson and Kleiner 2020; Kleiner and Xu 2022). However, despite this evidence, it remains unclear which aspects of licensing regulation impede mobility.

This paper, focusing on occupational mobility and building on work by Kleiner and Xu (2022) and related studies, examines occupational licensing at the extensive margin (existence) and intensive margin (qualifications) to determine which features of licensing policy underlie its negative impact on the occupational mobility of US workers. I use state-level data on occupational licensing policy matched to 2015–2022 Current Population Survey data on workers. The paper outlines a basic theoretical model to help guide the empirical analysis. Qualitatively consistent with the model and Kleiner and Xu (2022), I show that the existence of licensing regulation significantly lowers the probability of switching into an occupation by 2.2 percentage points (24 percent). However, the existence of licensing regulation does not significantly affect the probability of switching out of an occupation. The impact of licensing on occupation entry is robust to numerous sensitivity analyses and reflects an intention-to-treat estimate. This parameter is both policy relevant and methodologically valuable given possible concerns about using self-reported licensing status to estimate the average treatment effect on the treated parameter or a local average treatment effect through instrumental variables.

Analysis of several licensing qualifications suggests that the impact of extensive-margin licensing on occupation entry is caused by intensive-margin licensing regulations that specify fees and minimum thresholds for education and age, which can proxy for experience. This result also holds when accounting for the possibility that licensing also affects labor demand, not just labor supply. The intensive-margin effects of licensing on occupational mobility may help explain the weak relationship between licensing and product market safety and quality. Since the binding licensing qualifications likely have a mixed link to worker skills, licensing policy may have a limited ability to foster improvements in the product market.

The remainder of the paper is organized as follows. Section 2 outlines the theoretical model. Section 3 describes the data and creation of the sample used for analysis. Section 4 describes the strategy for identifying the impact of occupational licensing on occupational mobility. Section 5 presents the extensive-margin findings, and section 6 discusses the intensive-margin findings. Section 7 concludes.

2 A Model of Licensing and Occupational Mobility

To guide the empirical analysis, I outline a basic static model adapted from Johnson and Kleiner (2020). They develop a theoretical framework for the relationship between occupational licensing and interstate migration. This paper adjusts that framework to provide a theoretical basis for the relationship between occupational licensing and occupational mobility rather than mobility across geographies.

Within the same geographic labor market, individuals, i, decide between moving (switching) to a new occupation, m, or staying in the same occupation, s. Moving to a new occupation incurs a cost, c. Also, individuals have idiosyncratic preference shocks, ε_{im} and ε_{is}, specific to moving to a new occupation or staying in the same occupation. All workers in the model are employed.

Each individual cares about labor market earnings and knows with perfect certainty the earnings from staying in the same occupation, w_s, and the earnings from moving to a new occupation, w_m. Work hours, h, are fixed and normalized to 1. The price, p, of a fixed basket of market goods and services is also normalized to 1.

The (indirect) utilities of moving to a new occupation and staying in the same occupation are as follows:

$$U_{im} = w_m - c + \nu\varepsilon_{im},$$

$$U_{is} = w_s + \nu\varepsilon_{is}.$$

The preference shocks follow standard Gumbel distributions and are independently and identically distributed. The scale parameter, $\nu > 0$, determines the dispersion of those shocks. The occupational mobility rate is the fraction of individuals who choose to move to a new occupation, given by $\Pr(U_{im} > U_{is})$. As noted in Johnson and Kleiner (2020), who follow Dix-Carneiro, Soares, and Ulyssea (2018), and using the properties of Gumbel distributions, we can write the (log) occupational mobility rate as:

$$\log(MR) = \frac{1}{\nu}(V_m - c), \tag{1}$$

where $V_m = w_m - w_s$ is the earnings return to mobility.[1] Equation (1) is increasing in the relative gain, V_m, and decreasing in the cost, c. Thus, a higher relative earnings gain results in more people changing occupations, whereas a higher cost leads to more people staying in the same occupation.

[1] As Johnson and Kleiner (2020) note, the derivation of equation (1) is as follows: $MR = \mathrm{PR}(U_{im} > U_{is}) = \frac{e^{\frac{1}{\nu}(w_m - c)}}{e^{\frac{1}{\nu}(w_m - c)} - e^{\frac{1}{\nu}(w_s)}} \Rightarrow \frac{MR}{1-MR} = e^{\frac{1}{\nu}(w_m - w_x - c)} \Rightarrow \log(MR) \approx \log(\frac{MR}{1-MR}) = \frac{1}{\nu}(w_m - w_x - c)$ if $MR << 1$, which is typically the case.

To incorporate licensing into this framework, I allow for two types of occupations: licensed, L, and unlicensed, U. There are different costs of changing occupations that vary by licensing status. Specifically, no costs are associated with staying in the same occupation. There is a regulatory cost of moving to a licensed occupation, c^{RL}, but no such cost for moving to an unlicensed occupation (that is, $c^{RU} = 0$). There are also non-regulatory costs of moving to a licensed occupation, c^{NL}, or moving to an unlicensed occupation, c^{NU}. Regulatory costs are monetary, and non-regulatory costs are non-monetary or "psychic."

It is also helpful to distinguish licensing status "at baseline" (a start period) from licensing status "at final" (an end period) and related shares of individuals. In the model, a worker being employed in an occupation for which a license is (not) required is classified as (un)licensed. Let θ^{LL} be the share of workers licensed at baseline who are licensed at final, θ^{LU} is the share of workers licensed at baseline who are unlicensed at final, θ^{UU} is the share of workers unlicensed at baseline who are unlicensed at final, and θ^{UL} is the share of workers unlicensed at baseline who are licensed at final, with $\theta^{LU} = 1 - \theta^{LL}$ and $\theta^{UL} = 1 - \theta^{UU}$. Similarly, γ^{LL} is the share of workers licensed at final who are licensed at baseline, γ^{UL} is the share of workers licensed at final who are unlicensed at baseline, γ^{UU} is the share of workers unlicensed at final who are unlicensed at baseline, and γ^{LU} is the share of workers unlicensed at final who are licensed at baseline, with $\gamma^{UL} = 1 - \gamma^{LL}$ and $\gamma^{LU} = 1 - \gamma^{UU}$. As outlined in the analysis by Kleiner and Xu (2022), focusing on a worker's licensing status at final characterizes the impact of licensing on entry into an occupation, while focusing on the licensing status at baseline characterizes the impact of licensing on exit from an occupation.

The (log) occupational mobility rates for the four combinations of licensing status at baseline and licensing status at final are as follows:

$$\log(MR^{UL}) \approx \frac{1}{\nu}\Big(w_m^L - w_s^U - [c^{RL} + c^{NL}]\Big),$$

$$\log(MR^{LL}) \approx \frac{1}{\nu}\Big(w_m^L - w_s^L - [c^{RL} + c^{NL}]\Big),$$

$$\log(MR^{LU}) \approx \frac{1}{\nu}\Big(w_m^U - w_s^L - c^{NU}\Big),$$

$$\log(MR^{UU}) \approx \frac{1}{\nu}\Big(w_m^U - w_s^U - c^{NU}\Big).$$

I make the simplifying assumption that the earnings return from changing occupations does not vary by licensing status at baseline or final. Thus, $V_m^{UL} = V_m^{LL} = V_m^{LU} = V_m^{UU}$, where $V_m^{jk} = w_m^k - w_s^j$ for $j,k = \{U, L\}$.

Given that assumption, I can write the difference in (log) occupational mobility rates between licensed and unlicensed occupations as follows, first for entry:

$$\begin{aligned}\log(MR^L) - \log(MR^U) &= -\frac{1}{\nu}\Big(\gamma^{LL}[c^{RL} + c^{NL}] + [1-\gamma^{LL}][c^{RL} + c^{NL}] - \gamma^{UU}c^{NU} - [1-\gamma^{UU}]c^{NU}\Big)\\ &= -\frac{1}{\nu}(c^{RL} + c^{NL} - c^{NU}),\end{aligned} \tag{2}$$

and for exit:

$$\log(MR^L) - \log(MR^U) = -\frac{1}{\nu}\Big(\theta^{LL}[c^{RL}+c^{NL}] + [1-\theta^{LL}]c^{NU} - \theta^{UU}c^{NU} - [1-\theta^{UU}][c^{RL}+c^{NL}]\Big). \tag{3}$$

In equation (2), focused on entry into occupations, the difference in (log) occupational mobility rates between workers in licensed and unlicensed occupations is a negative function of the regulatory cost of moving to a licensed occupation, c^{RL}, and likewise a negative function of the relative "risk aversion" cost of occupational mobility, $c^{NL} - c^{NU}$. One would observe $c^{NL} > c^{NU}$ if people with high risk aversion (also assumed to have a high aversion to occupational mobility) tend to self-select into licensed occupations. If such selection occurs and $c^{NL} - c^{NU}$ is also sufficiently large relative to c^{RL}, then comparing occupational mobility rates of licensed and unlicensed workers in equation (2) will yield negatively biased estimates of the effect of licensing regulatory costs, c^{RL}, on entry into licensed occupations. Thus, to account for the non-monetary costs of occupational mobility, the model suggests that the estimation should control for individual-level traits that might affect both licensing status and the probability of occupational mobility.

In equation (3), focused on exit from occupations, the aforementioned discussion still applies regarding the relative risk aversion cost of occupational mobility, $c^{NL} - c^{NU}$. However, predictions are ambiguous for the sign and magnitude of equation (3), and they are ambiguous for how the expression varies with changes in licensing regulatory costs, c^{RL}. This uncertainty arises from the terms θ^{LL} and θ^{UU} not dropping out of equation (3), as γ^{LL} and γ^{UU} do in equation (2). It is illustrative to examine a few values of θ^{LL} and θ^{UU}. For instance, if $\theta^{LL} = \theta^{UU} = 1$, reflecting that no workers change status from licensed to unlicensed or unlicensed to licensed, then equations (2) and (3) are identical. Alternatively, if $\theta^{LL} = \theta^{UU} = 0$, corresponding to every worker changing status from licensed to unlicensed or unlicensed to licensed, then equations (2) and (3) are equal in magnitude but opposite in sign. And if $\theta^{LL} = \theta^{UU} = 0.5$ (half of the workers change licensing status), $\theta^{LL} = 1$ and $\theta^{UU} = 0$ (all workers are licensed at final), or $\theta^{LL} = 0$ and $\theta^{UU} = 1$ (all workers are unlicensed at final), then equation (3) equals 0.

In the data, θ^{LL} and θ^{UU} are strictly between 0.5 and 1—specifically, 0.96 in both cases. Thus, one might expect an empirical analog of equation (3) to have the same sign as an empirical analog of equation (2) but a smaller magnitude, closer to 0. This also suggests more definitive analysis can be achieved by focusing on entry effects rather than exit effects. More generally, the model supports the notion that a cross-sectional comparison of occupational mobility rates between licensed and unlicensed occupations—separately for entry and exit—can be used to identify the impact of licensing regulation on occupational mobility. However, given some of the model's limitations, such as omitting heterogeneity across states and allowing minimal heterogeneity across occupations, the identification strategy will be discussed further in section 4.

3 Data on Occupational Licensing and Workers

3.1 Data on State-Level Occupational Licensing Policy

Data on occupational licensing at the extensive margin (existence) and intensive margin (qualifications) come from Carpenter II et al. (2017) and Knepper et al. (2022). These reports, which have been referenced individually and as a full series by policy and academic sources (for instance, Kleiner and Soltas 2023; National Conference of State Legislatures 2012), assess state-level licensing regulations for 102 selected occupations. The set of examined jobs in the second and third reports, from 2017 and 2022, evolved from sampling for the first report in 2012 (Carpenter II et al. 2012). The authors compiled the initial set of occupations in 2012—a different set of 102 jobs—using a list of licensed occupations from CareerOneStop, the career website sponsored by the US Department of Labor. They further narrowed the list to a set of "recognized" occupations by dropping jobs that did not overlap with occupational lists maintained by the US Bureau of Labor Statistics (BLS). The authors finalized the list by excluding jobs with average earnings above the national average earnings, resulting in a set of 102 low-earnings and middle-earnings occupations, all of which required a license in at least one state at the time (Knepper et al. 2022).

Revisions to that set of occupations in the 2017 report limit comparability with the jobs in the 2012 report. Accordingly, a comparison data set between the two reports links only 45 occupations. This paper therefore focuses on occupations in the 2017 and 2022 reports. All 102 sampled jobs are comparable across those two editions given that revisions to the methods for the 2022 report were only minor.

The report data contain information on extensive-margin licensing, reflecting the existence of licensing regulations in a state-occupation pairing, as well as intensive-margin licensing, reflecting the licensing qualification(s) in a state-occupation. For extensive-margin licensing, some licenses documented in the report reflect sole proprietors while other licenses reflect workers. In the former case, linked data on workers are restricted to people who are self-employed. For intensive-margin licensing, the selected qualifications in the report were chosen because they are relatively common across examined occupations. Of those qualifications, this paper focuses on fees (converted to constant 1999 US thousands of dollars), number of exams, minimum-grade thresholds (for instance, 10th-grade or 12th-grade/high school completion), and minimum-age thresholds in years (a potential proxy for worker experience).[2]

3.2 Data on Worker Occupations and Characteristics

Individual-level data on occupational choices and other characteristics are taken from the Current Population Survey (CPS). The CPS, which was started in 1940 to measure national unemployment, is the main source of labor force statistics for the United States and is sponsored jointly by the US Census Bureau and the BLS. The Basic Monthly Survey (BMS) component of the CPS relies on a rotating sample of 60,000 households, whose responses on numerous topics refer to activities during the preceding week that includes the 12th of the month. Households are in the CPS for four consecutive months, out for eight months, and then return for four months before leaving the sample permanently (United States Census Bureau 2006). With this 4-8-4 design, the BMS has the scope to be used as a longitudinal survey, although it is typically used as a pooled cross section. The Minnesota Population Center provides CPS data as part of its online Integrated Public Use Microdata Series (IPUMS) (Flood et al. 2022). The center's website and linking methods greatly facilitate use of the longitudinal features of the BMS for research (Drew, Flood, and Warren 2014).

Importantly for linking these worker data to the licensing-policy data, the BMS contains information on the year, state of residence (which does not change by construction, thus eliminating geographic mobility), and occupation of current employment or, for nonemployed workers, past employment (within the past year for people who are not in the labor force). I compare a worker's occupation in the first month-in-sample (MIS) with the occupa-

[2]The sole excluded qualification, "days lost," quantifies education and experience requirements and is omitted because it maps less directly to the underlying criteria compared with the four included qualifications.

tion in the eighth MIS 15 months later to determine if any change in occupation has occurred. Occupations are classified at a four-digit level, although most of the variation occurs at a three-digit level. For example, "barbers" is OCC2010=4500 and the next available occupational category is OCC2010=4510, "hairdressers, hairstylists, and cosmetologists." The data also contain additional individual characteristics such as demographics and educational attainment, which may assist with characterizing differences in the non-monetary costs of occupational mobility (see section 2).

The CPS data also contain information on self-reported licensing status from 2015 onward.[3] Given concerns about potential measurement error if using licensing-policy information for intensive-margin licensing and self-reported licensing status for extensive-margin licensing (especially since the self-reported measure is not limited to state-issued licenses), I use licensing-policy information for the main analysis. However, I use self-reported licensing status for some supplementary analysis and thus restrict the CPS data to January 2015 through December 2022 (sample counts are prohibitively small in 2023). As detailed further in the next section, this period restriction also helps facilitate linking worker data to licensing-policy data since the latter are from 2017 and 2022.[4]

3.3 Sample Selection

Initial sample restrictions related to CPS data quality and subsequent sample restrictions to link licensing-policy data and determine worker subsamples are presented in Appendix

[3] I indicate that a worker self-reports as licensed if they responded "yes" to both of the following CPS questions: (1) "Do you have a currently active professional license or a state or industry license?" and (2) "Were any of your certifications or licenses issued by the federal, state, or local government?" This definition of self-reported licensing status aligns with those of Kleiner and Soltas (2023) and other studies. Unlike Kleiner and Xu (2022), I do not incorporate a third CPS licensing question, available from 2016 onward, about whether the certification or license in question is required for one's job. Such incorporation restricts the sample to one less year without much benefit regarding the reduction of possible measurement error (due to someone being coded as self-reporting as licensed based on, for instance, a license for a secondary occupation or a license that has not yet expired for a previously held occupation).

[4] Opting for the licensing-policy data has additional value if one is concerned that some of the self-reported licensing variation may not be driven by licensing-policy variation. Some studies propose instrumental-variable strategies to try focusing on the desired licensing-policy variation (for instance, Kleiner and Soltas 2023 and Kleiner and Xu 2022). Instead, this paper directly uses licensing-policy variation.

Tables A1 and A2. Some restrictions are minimally binding, if at all, but are imposed for assurance purposes. The subsample of workers unemployed in the first MIS was retained for the construction of descriptive weights but ultimately dropped from the analysis because the sample was small. I further limit the analysis to workers who are employed at final due to a similar, small-sample concern.

To link licensing-policy data to CPS workers at the state-occupation-period level, I designate the 2017 policy data to correspond to 2015–2019 CPS data and designate the 2022 policy data to correspond to 2020–2022 CPS data. These designations are partly based on the timing of licensing-policy data collection. For instance, for the 2022 report, the collection period was February 2020 through March 2022, including a final check to ensure all data remained current at the close of data collection. If one assumes gradual policy change as well, then a two-year CPS window before and after a report year seems reasonable for data-linking purposes. Matching states across the data sources is straightforward, thus leaving only the matching of occupations.

To link occupations in the licensing-policy data to CPS occupations, I first create a crosswalk matching licensing-policy occupations to O*NET occupations.[5] I then match O*NET occupations to Standard Occupation Classification (SOC) occupations and SOC occupations to CPS occupations (OCC codes in Flood et al. 2022) using existing crosswalks available from the BLS. Lastly, I match different occupation codes in the CPS (OCC and OCC2010) using existing linkages by Flood et al. (2022). I assess match quality for each of those stages and impose restrictions to ensure each occupation meets the criteria for sufficient match quality (see Appendix Table A2).

As noted in Tables 1 and 2, the resulting sample spans eight years of analyzed workers from 2015 through 2022 and reflects 54 occupations and 12,004 workers. The worker characteristics from the CPS shown in Table 2 help highlight differences between the groups of analyzed and unanalyzed workers. For instance, as measured at final and consistent with

[5] As noted on their website, the O*NET database maintains information on occupations, including related skills, knowledge, and work activities.

aggregate statistics, 31.0 percent of analyzed workers report being licensed compared with 24.1 percent of unanalyzed workers. Among the additional disparities, analyzed workers are notably less likely to have a bachelor's degree or higher level of education and notably more likely to work in occupations reflecting construction, health-care support, and personal care and service.

Given such selection resulting from numerous sample restrictions, I create descriptive weights for all workers in the sample. These weights incorporate both a CPS sample design weight and a post-stratification weight; the latter is intended to capture inadvertent sample selection along various dimensions including sex, education, and area (see Appendix). With the weights applied, sample statistics for share measures reasonably reflect the national population of interest.[6] Regarding unweighted counts, the sample contains 12,004 workers, of which 6,230 are licensed at baseline and 5,774 are unlicensed at baseline. At final, 6,227 of those workers are licensed and 5,777 are unlicensed (see Table 2 and Appendix Table A3).

4 Identifying the Impact of Licensing on Mobility

I use the information on occupational licensing policy linked to data on worker occupations and other traits to identify the impact of occupational licensing on occupational mobility. Motivated by the model (see section 2), I can use a cross-sectional comparison of occupational mobility rates between licensed and unlicensed occupations—separately for entry and exit—in addition to individual-level controls to account for psychic costs. However, further work is needed to address some limitations of the simple model, such as the lack of heterogeneity across states and limited allowance for heterogeneity across occupations.

By outlining an example using the potential outcome framework, I can illustrate how such heterogeneity might matter for econometric identification. Suppose one were to estimate the occupational mobility of barbers in Massachusetts (MA) compared with the occupational

[6] In validity checks, the sample with weights applied closely replicates targeted population statistics such as the share that is female (0.51 in 2019 according to census estimates and estimated as 0.50 in the sample).

mobility of veterinary technicians in Vermont (VT). According to the 2022 licensing-policy data, the former case is a licensed state-occupation pairing while the latter case is an unlicensed state-occupation pairing. Let $L = \{0, 1\}$ be an indicator for being in a licensed state-occupation and $Y = \{0, 1\}$ be an indicator for switching occupations. Also, let Y_1 and Y_0 reflect treated (licensed) and untreated (unlicensed) outcomes, respectively. Thus, whether for entry or exit, a cross-sectional comparison of occupational mobility rates for Massachusetts barbers and Vermont veterinary technicians would estimate the difference between $\mathbb{E}[Y_1|L = 1]$ (Massachusetts barbers) and $\mathbb{E}[Y_0|L = 0]$ (Vermont veterinary technicians).

However, to estimate the impact of licensing policy on occupational mobility, the ideal counterfactual for Massachusetts barbers would be $\mathbb{E}[Y_0|L = 1]$, which would allow identification of the average treatment effect on the treated (ATT), $\mathbb{E}[Y_1 - Y_0|L = 1]$. The unobserved object, $\mathbb{E}[Y_0|L = 1]$, reflects the occupational mobility rate for Massachusetts barbers if they were unlicensed. Biased estimation occurs if there is any disparity between $\mathbb{E}[Y_0|L = 1]$ for barbers in Massachusetts (the ideal counterfactual) and $\mathbb{E}[Y_0|L = 0]$ for veterinary technicians in Vermont (the utilized counterfactual). Such bias can be further decomposed into the following potential sources of endogeneity:

1. <u>Occupation</u>: $Barber, MA : \mathbb{E}(Y_0|L = 1) - VetTech, MA : \mathbb{E}(Y_0|L = 1) \neq 0$
2. <u>State</u>: $Barber, MA : \mathbb{E}(Y_0|L = 1) - Barber, VT : \mathbb{E}(Y_0|L = 1) \neq 0$
3. <u>Treatment</u>: $Barber, MA : \mathbb{E}(Y_0|L = 1) - Barber, MA : \mathbb{E}(Y_0|L = 0) \neq 0$

If occupations or states with higher rates of occupational mobility are more likely to have licensing policy, perhaps as a potential protection for licensed workers, one would expect upward bias on estimates of the impact of licensing on occupational mobility. To address this possibility of bias from the first and second sources, I can include occupation and state indicators as controls in the estimation. The third potential source of bias is a concern only to the extent that state-level enactment of licensing policy is nonrandom with respect to occupational mobility, which is not a determinant typically highlighted.[7] However, if such endogeneity exists, it may similarly lead to upwardly biased impact estimates if licensed state-occupations are more likely to have higher rates of occupational mobility. I can examine robustness checks regarding this concern, including estimation with state × occupation indicators, which limits identification to variation in licensing policy within state-occupations over time. Since such an approach would require a large number of estimation degrees of freedom given the count of states and occupations analyzed, I can alternatively pursue less stringent inclusion of state × occupation-group indicators or region (census division) × occupation indicators. Such indicators limit identification to variation in licensing policy within state-occupation groups over time or within region-occupations over time, respectively, as explored by Kleiner and Soltas (2023).

I estimate the following cross-sectional specifications for worker i and timing in the baseline MIS b to examine exit effects, or timing in the final MIS f to examine entry effects, using weighted least squares (WLS):

$$Y_{fi} = \omega + \beta L_{fi} + \mathbf{O}'_{fi}\alpha + \mathbf{S}'_{fi}\gamma + \mathbf{X}'_{fi}\theta + \varepsilon_{fi}, \tag{4}$$

$$Y_{fi} = \omega + \beta L_{bi} + \mathbf{O}'_{bi}\alpha + \mathbf{S}'_{bi}\gamma + \mathbf{X}'_{bi}\theta + \varepsilon_{bi}. \tag{5}$$

Y_{fi} is an indicator for having switched occupations between the initial and final MIS, which are 15 months apart. For most of the analysis, L_{fi} and L_{bi} are treatment indicators for a worker being in a licensed state-occupation in the final MIS (entry) or baseline MIS (exit), respectively. However, in some analysis of intensive-margin licensing, L_{fi} and L_{bi} reflect continuous licensing qualifications, such as fees or exams. $\mathbf{O}_{fi}$ and $\mathbf{O}_{bi}$ reflect vectors of occupation indicators at final and baseline, respectively, while $\mathbf{S}_{fi}$ and $\mathbf{S}_{bi}$ reflect vectors of state indicators at final and baseline, respectively. $\mathbf{X}_{fi}$ and $\mathbf{X}_{bi}$ correspond respectively to vectors of remaining controls at final and baseline—namely, age, education, period, race/ethnicity,

[7]For instance, Carollo et al. (2022) find that the adoption of licensing regulations is more likely for occupations that pose a greater risk to consumers, are in larger markets, or have a state professional association.

industry, and other characteristics (sex, marital status, any children, and any children under age 5). Heteroskedasticity-robust standard errors are included in the estimation. As outlined in the model (see section 2), if licensing reduces occupational mobility, then estimates of β will be negative. The weights in WLS estimation are CPS weights reflecting survey sample design further adjusted for post-stratification sample selection (see Appendix).

Assuming the licensing-policy measures, L_{fi} and L_{bi}, are exogenous in specifications (4) and (5), the entry and exit estimates of β are reduced-form coefficients reflecting an intention-to-treat (ITT), which may be more relevant for policy guidance than an ATT. Nevertheless, robustness analysis can also explore the possibility of using licensing policy as an instrument for self-reported licensing to yield a local average treatment effect (LATE) instead (Imbens and Angrist 1994). This LATE could also reflect an ATT if the impact of licensing on occupational mobility is homogeneous for all treated workers and not distinct for LATE "compliers" induced to self-report as licensed due to licensing policy. Figure 1 shows that workers in licensed state-occupations are indeed more likely to self-report as licensed compared with workers in unlicensed state-occupations, as expected. However, this relationship is not very strong, as the share self-reporting as licensed is much lower than 1 in licensed state-occupations (perhaps due to measurement error or actual behavior such as imperfect policy enforcement) and much higher than 0 in unlicensed state-occupations (perhaps due to measurement error or actual behavior such as voluntary licensing). Thus, the proposed instrumental variables (IV) estimation may not prove feasible due to a weak first stage.

5 Impact of Extensive-Margin Licensing on Mobility

5.1 Descriptive Patterns

Figure 2 displays scatterplots to illustrate the correlation between the share of an analyzed occupation that is licensed by state-occupation policy and the share of workers in the occupation experiencing occupational mobility between the analyzed occupations ("analyzed mobility" in the figure title), separately for entry and exit. There is only a mild correlation between licensing policy and occupational mobility, with slope coefficients of 0.04 (entry) and –0.01 (exit). Although the absence of a strong correlation need not imply the absence of a causal relationship given potentially important controls in causal estimation, this finding contrasts with stronger negative correlations for entry and exit found by Kleiner and Xu (2022).

Exploring this relationship further, Figure 3 depicts scatterplots of the correlation between the share of any CPS occupation ("all occupations" in the figure title, totaling 442 in number) that is licensed according to self-reporting and the share of workers in the occupation experiencing occupational mobility between any CPS occupation ("all mobility" in the figure title), separately for entry and exit. In both plots, a much stronger negative correlation is now observed, with slope coefficients of –0.39 (entry) and –0.41 (exit). Comparing Figures 2 and 3 reveals that three factors differ: the set of occupations, how licensing is measured, and how occupational mobility is measured. A further assessment of Appendix Figures A1 and A2 suggests that the key factor explaining the difference between Figures 2 and 3 is how occupational mobility is measured—namely, the size of the occupational network underlying that measure. Thus, robustness analysis will examine whether such network size affects causal estimates as well.

5.2 Main Results

Turning to the causal impact of licensing on occupational mobility, Tables 3 and 4 display treatment effects for entry and exit, respectively. The mean value of the licensing indicator shows that 52 percent of workers in both samples are in licensed state-occupations, and the unlicensed mean of 9 percent of workers changing occupations is fairly consistent with external estimates.[8] Columns (1) and (2) of both tables reveal that ordinary least squares

[8]Using CPS data from January 2003 through 2004 and detailed occupational categories, Shniper (2005) estimates 7.2 percent of employed workers age 16 and older changed occupations within a year.

(OLS) and WLS estimates are similar, with even slightly larger standard errors for WLS. As noted by Solon, Haider, and Wooldridge (2015), such equivalence helps support the idea that the model is correctly specified because both estimators are consistent when the necessary conditions are met.

Columns (3) through (7) allow for various combinations of occupation, state, and other controls. As hypothesized, omitting occupation and state indicators results in upward bias on the licensing-mobility entry effect, especially in the case of occupation indicators. Controlling for additional worker characteristics in preferred specification (7) barely changes the estimated coefficient, suggesting limited worker selection due to non-monetary costs. The existence of licensing regulation in a state-occupation significantly decreases worker entry into the occupation by 2.2 percentage points, reflecting a 24 percent decline in the probability of switching into an occupation. Effects on exit from an occupation are similarly negative but smaller in magnitude, as predicted by the model (see section 2). The existence of licensing regulation in a state-occupation decreases worker exit from the occupation by 1.2 percentage points, which is a 13 percent decline in the probability of switching out of an occupation. However, this effect is not statistically significant. Accordingly, the remainder of the paper focuses on entry effects.

These intention-to-treat estimates are not directly comparable to the estimates in Kleiner and Xu (2022). In that study, the use of self-reported licensing in OLS and IV estimation results in ATT and LATE parameters. Regarding the latter, the study's estimates suggest that licensing decreases occupational mobility by 5.1 to 6.6 percentage points for entry and decreases such mobility by 1.1 to 1.2 percentage points for exit, although the latter is not significant. The sign and statistical significance (or lack thereof) of those results qualitatively align with this paper's findings. Additionally, in robustness analysis, Kleiner and Xu (2022) use an indicator for a worker's being in a universally licensed occupation as the licensing measure rather than self-reported licensing. The universally licensed measure is closer to the licensing measure used in this study than the self-reporting measure is, although analysis with the universally licensed measure uses a control group that is a mix of workers in licensed and unlicensed state-occupations rather than the latter only. Using this alternative treatment, Kleiner and Xu (2022) find that licensing reduces occupational entry by 1.5 percentage points. That result is similar to this paper's findings and expectedly smaller in magnitude given the mixed licensing status of workers in the control group.

5.3 Sensitivity

Table 5 shows the sensitivity of the effect of licensing on entry into an occupation by including several alternative specifications. Column (1) shows that any data quality improvements that may result from restricting the sample to workers who participate in the survey for all eight months-in-sample have a minimal impact on the licensing-mobility entry estimate or its precision. Column (2) reveals that replacing state and occupation indicators with state $\times$ occupation indicators increases the standard error by an order of magnitude. This suggests that the absence of a significant coefficient in this specification may be due to insufficient degrees of freedom for estimation, as hypothesized earlier. Alternatively, columns (3) and (4) use region $\times$ occupation indicators instead of occupation indicators and state $\times$ occupation-group indicators instead of state indicators, respectively. Both results provide some evidence of endogenous licensing policy, as supported by a more negative licensing-mobility entry effect that ranges from –2.5 to –4.5 percentage points.

Columns (5) and (6) explore how the primary analysis might be affected given the restriction to a network of 54 analyzed occupations. Column (5) adds indicators for the occupation at baseline to further account for occupational composition.[9] Column (6) creates a sample focused solely on entry by adjusting sample restrictions and weights accordingly. Specifically, I allow for any CPS occupation at baseline but only the 54 analyzed occupations at final, in contrast to the primary analysis that restricts both the baseline and final occupation to be one of the 54 analyzed occupations. As Table 5 shows, the limited occupation network in

[9] Including all pairwise combinations of occupation indicators instead results in a large number of parameters to estimate.

the primary analysis has minimal influence on the estimated licensing-mobility entry effect.

Columns (7) and (8) examine whether labor demand effects of licensing policy play any role in the main findings, in addition to the theorized labor supply effects. The existence of licensing regulation in a state-occupation may provide a signal of product safety and/or quality to consumers, thus increasing labor demand and potentially increasing entry into an occupation. Kleiner and Soltas (2023) theorize and show that such a signal is likely more valuable in occupations that more commonly require a license. Consistent with their study, the licensing-mobility entry effect for occupations that more commonly require a license is smaller (–1.4 percentage points) and no longer significant, while the entry effect for occupations that less commonly require a license is larger (–4.4 percentage points) and significant. This pattern of results may reflect an increase in labor demand reducing the size of the negative licensing-mobility entry effect for occupations that more commonly require a license.

Lastly, column (9) uses self-reported licensing status as an alternative licensing measure, while column (10) explores the feasibility of using licensing policy as an instrument for self-reported licensing status by estimating the IV first stage. Column (9) shows that self-reported licensing actually has a significantly positive impact on entry into an occupation. This result suggests large possible upward bias in the paper's estimation sample from using the self-reported licensing measure and further supports the use of a licensing-policy measure instead. This finding also supports the pursuit of IV estimation in other research that uses self-reported licensing as a regressor (for instance, IV estimation in Kleiner and Soltas 2023 and Kleiner and Xu 2022), although some caution may be warranted if the utilized instruments rely on a subset of the variation in the self-reported licensing measures. Column (10) shows that licensing policy is positively related to self-reported licensing. However, this first-stage relationship is too weak to enable IV estimation, as being in a licensed state-occupation leads to an increase of only 1.4 percentage points in the probability of self-reporting as licensed. Still, taking the estimates in columns (9) and (10) at face value provides reasoning for why using self-reported licensing measures may underestimate the ATT licensing-entry effect. That said, the findings of Kleiner and Xu (2022) suggest overestimation of the ATT could also occur when using self-reported licensing.

6 Impact of Intensive-Margin Licensing on Mobility

6.1 Main Results

Having established the impact of extensive-margin licensing on occupational mobility and having compared the findings to those of Kleiner and Xu (2022), the paper now explores the impact of intensive-margin licensing on occupational mobility. Such analysis will help in understanding what drives the extensive-margin licensing-mobility entry effect. Table 6 displays the extensive-margin entry coefficient as well as coefficients from using four distinct measures of intensive-margin licensing: licensing fees (in constant 1999 thousands of US dollars, converted using the Consumer Price Index for All Urban Consumers from the BLS), the number of licensing exams, and the minimum thresholds for a licensed worker's school grade and age. For all of those measures of licensing qualifications, the value of the measure equals 0 for unlicensed state-occupations and licensed state-occupations that do not impose a given qualification. In the sample, the unconditional mean values for those intensive-margin measures are \$136 for fees (ranging from \$0 to \$2,186), 0.5 for the number of exams (ranging from 0 to 6), 0.9 for the minimum grade (ranging from 0 to 12), and 6.1 for the minimum age in years (ranging from 0 to 21).[10]

The table shows that increasing licensing fees by \$1,000, which is roughly seven times the average amount, significantly decreases the probability of occupation entry by 1.8 percentage points. There is no significant effect of the number of licensing exams on switching into an

[10]Based on Knepper et al. (2022), the average values for the intensive-margin licensing measures when conditioning on non-zero values (measured at the state-occupation level for the 54 analyzed occupations and not at the worker level in the estimation sample) are \$188 for fees (in 1999 US dollars), 1.8 exams, an 11.5 minimum grade, and an 18.2 minimum age.

occupation (inclusive of the effect of a change from no exams to one exam). Increasing the minimum education requirement by one grade level, which is roughly the mean value, significantly decreases the probably of entering an occupation by 0.2 percentage point. Lastly, increasing the minimum age threshold by one year, which is approximately one-sixth of the mean value, significantly decreases the probability of occupation entry by 0.1 percentage point. The fees mechanism has an unclear link to worker skills and the assumed resultant safety and quality of goods and services, while the minimum-grade and minimum-age mechanisms have more clear links to such worker skills and resultant product safety and quality. This result—the mixed link to worker skills for the intensive-margin qualifications that drive the extensive-margin licensing-mobility entry effect—may help explain the lack of a consensus across studies that examine the effect of licensing regulations on product safety and quality.[11]

To further present these intensive-margin effects, Table 7 stratifies the positive values of each licensing qualification (omitting exams) into two bins—a below-median bin and an at-or-above-median bin. The relevant median values are $139 for fees (in 1999 US dollars), 12th grade for the minimum grade, and 18 years old for the minimum age. The licensing measure is now an extensive-margin indicator for being in a licensed state-occupation, and control group workers (unlicensed workers and licensed workers in a state-occupation that does not impose the given licensing qualification) are approximately constant across strata for each intensive-margin measure.[12] Consistent with Table 6, Table 7 shows that significantly negative and larger licensing-mobility entry effects occur for licensed state-occupations with qualifications that are at or above the median level rather than below the median level. Having higher licensing fees decreases the probability of occupation entry by 2.6 percentage points, while having higher licensing minimum-age thresholds reduces the probability of occupation entry by 1.6 percentage points. The minimum-grade coefficient in the at-or-above-median strata

[11] Sweetland and Carpenter II (2022) provide a helpful survey of this literature.

[12] The count of control group workers is not exactly constant across strata for each intensive-margin measure due to dropped singleton observations in the estimation.

is nearly statistically significant at the 10 percent level and perhaps might be significant at a higher threshold value (not available in the data) given the distribution of this measure.

Additionally, estimating intensive-margin licensing effects may allow for an alternative approach to account for the possible role of labor demand. One might reasonably assume that intensive-margin licensing variation does not shift labor demand because such information on licensing qualifications may be relatively unobserved by consumers as compared with the extensive-margin licensing variation on the existence of regulations for a state-occupation. Under that assumption, comparing estimates across strata for each qualification in Table 7 would yield demand-constant estimates of the licensing-mobility entry effect. Increasing licensing fees from a level that is below median to a level that is at or above median decreases the probability of entering an occupation by 1.5 percentage points. Likewise, increasing the licensing minimum age from the below-median level to the at-or-above-median level decreases the probability of occupation entry by 1.1 percentage points. Thus, whether one considers high-strata estimates or between-strata estimates (demand-constant) from Table 7, the extensive-margin licensing-mobility entry effect of –2.2 percentage points is significantly and comparably driven by intensive-margin fees and minimum-age thresholds, although to a slightly greater extent regarding fees.

6.2 Characterizing Impact

Table 8 further characterizes the impact of high intensive-margin licensing qualifications on occupational mobility along three dimensions of heterogeneity: occupational group, industry, and region (census division). Column (1) shows that being in an occupation that requires a license with a high fee significantly reduces the probability of occupation entry for the construction industry as well as several regions—New England, Middle Atlantic, West South Central, and Pacific. However, high fees significantly raise the probability of occupation entry for the fire, insurance, and real estate industry, perhaps indicating the presence of positive labor demand licensing effects. (And it should be noted that the coefficient is marginally statistically significant at the 10 percent level.) Column (2) of the table illustrates that a high minimum-grade threshold significantly lowers the probability of switching into an occupation for jobs in the "Other" occupational group and into the industries reflecting various services and public administration.[13] While some of these licensing-mobility entry effects are quite large, they are also estimated relatively imprecisely. The final column of Table 8 shows that a high minimum-age requirement significantly decreases the probability of entering an occupation for the various-services industry as well as the New England and Pacific regions.

For some categories of heterogeneity, including the various-services or public-administration industries, licensing qualifications that seem linked to worker skills (and thus possibly linked to improved product safety or quality) are the mechanisms underlying the estimated decrease in occupational mobility due to the existence of licensing regulations. When considering social welfare, this trade-off between the labor market and the product market may prove to be worthwhile upon closer assessment. However, for other categories of heterogeneity such as the construction industry, licensing qualifications that seem less tied to worker skills are the mechanisms driving the negative licensing-mobility effect. In such cases, a social welfare assessment might not support retaining licensing regulations in their current form given the impact of the policy in labor and product markets. Finally, for some categories of heterogeneity such as the New England and Pacific regions, licensing qualifications with a collective mixed link to worker skills are the mechanisms responsible for the negative licensing-mobility effect. In such cases, it may be more difficult to predict the outcome of a social welfare assessment regarding licensing policy. That outcome may depend on additional details that govern which licensing qualification matters most in a given case. Regardless, further examination of the welfare considerations in a particular scenario, as generally analyzed by work such as that of Kleiner and Soltas (2023), would be advisable to help guide effective licensing policy.

[13]The occupations in the "Other" occupational group are bill collection agency, funeral attendant, sign language interpreter, unarmed security guard, and title examiner.

7 Conclusion

This paper uses data on US workers matched to licensing-policy data to estimate the impact of occupational licensing at the extensive margin (existence) and intensive margin (qualifications) on occupational mobility. Consistent with a basic model, I find that the existence of licensing regulation significantly reduces the probability of entry into an occupation by 2.2 percentage points (24 percent) but does not significantly affect the probability of exit from an occupation. The licensing-mobility entry effect reflects a policy-relevant intention-to-treat estimate and is robust to various sensitivity checks. Analysis of select licensing qualifications suggests that the impact of extensive-margin licensing on occupation entry is driven by intensive-margin licensing regulations that govern fees and minimum thresholds for education and age, which can proxy for experience. This result holds when accounting for potential labor-demand effects of licensing and may help explain the weak relationship between licensing and product-market safety and quality. Such reasoning stems from the licensing qualifications likely having a mixed link to worker skills, the presumptive mechanism through which licensing regulations could foster product-market improvements.

Thus, licensing policy may benefit from further assessments of the licensing qualifications that drive labor market outcomes such as occupational mobility. Such assessments would help identify the likely link between licensing qualifications and worker skills, thus aiding determination of social welfare and whether there are positive net benefits from licensing policy reform. This licensing reform could involve changes in the structure of licensing, government and private alternatives (for instance, certification, registration, bonding and insurance, product reviews), or both. Future research directly examining licensing effects in both labor and product markets would also be beneficial. Such analysis would help quantify the link between licensing qualifications, worker skills and traits, and the safety and quality of goods and services, thereby further guiding effective policy.

References

Carollo, Nicholas A., Jason F. Hicks, Andrew Karch, and Morris M. Kleiner. 2022. "The Origins and Evolution of Occupational Licensing in the United States." Working paper.

Carpenter II, Dick M., Lisa Knepper, Angela C. Erickson, and John K. Ross. 2012. *License to Work: A National Study of Burdens from Occupational Licensing.* Arlington, VA: Institute for Justice.

Carpenter II, Dick M., Lisa Knepper, Kyle Sweetland, and Jennifer McDonald. 2017. *License to Work: A National Study of Burdens from Occupational Licensing.* Arlington, VA: Institute for Justice.

Dix-Carneiro, Rafael, Rodrigo R. Soares, and Gabriel Ulyssea. 2018. "Economic Shocks and Crime: Evidence from Brazilian Trade Liberalization." *American Economic Journal: Applied Economics* 10(4): 158–195.

Drew, Julia A. Rivera, Sarah Flood, and John Robert Warren. 2014. "Making Full Use of the Longitudinal Design of the Current Population Survey: Methods for Linking Records Across 16 Months." *Journal of Economic and Social Measurement* 39: 121–144.

Flood, Sarah, Miriam King, Renae Rodgers, Steven Ruggles, J. Robert Warren, and Michael Westberry. 2022. "Integrated Public Use Microdata Series, Current Population Survey: Version 10.0 [data set]." Minneapolis, MN: IPUMS. https://doi.org/10.18128/D030.V10.0.

Imbens, Guido W., and Joshua D. Angrist. 1994. "Identification and Estimation of Local Average Treatment Effects." *Econometrica* 62(2): 467–475.

Jackson, Osborne. 2021. "Job Displacement and Sectoral Mobility." Research Department Working Paper 21-19. Boston, MA: Federal Reserve Bank of Boston.

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.

Kleiner, Morris, and Ming Xu. 2022. "Occupational Licensing and Labor Market Fluidity." Working paper.

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): S173–S202.

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.

Knepper, Lisa, Darwyyn Deyo, Kyle Sweetland, Jason Tiezzi, and Alec Mena. 2022. *License to Work: A National Study of Burdens from Occupational Licensing.* Arlington, VA: Institute for Justice.

National Conference of State Legislatures. 2012. “The State of Occupational Licensing: Research, State Policies and Trends.” Washington, DC: National Conference of State Legislatures.

Shniper, Lynn. 2005. “Occupational Mobility, January 2004.” *Monthly Labor Review* 128(12): 30–35.

Solon, Gary, Steven J. Haider, and Jeffrey M. Wooldridge. 2015. “What Are We Weighting For?” *Journal of Human Resources* 50(2): 301–316.

Sweetland, Kyle, and Dick M. Carpenter II. 2022. *Raising Barriers, Not Quality: Occupational Licensing Fails to Improve Services.* Arlington, VA: Institute for Justice.

United States Census Bureau. 2006. “Current Population Survey: Design and Methodology, Technical Paper 66.” Available from US Census website: https://www.census.gov/prod/2006pubs/tp-66.pdf (October).

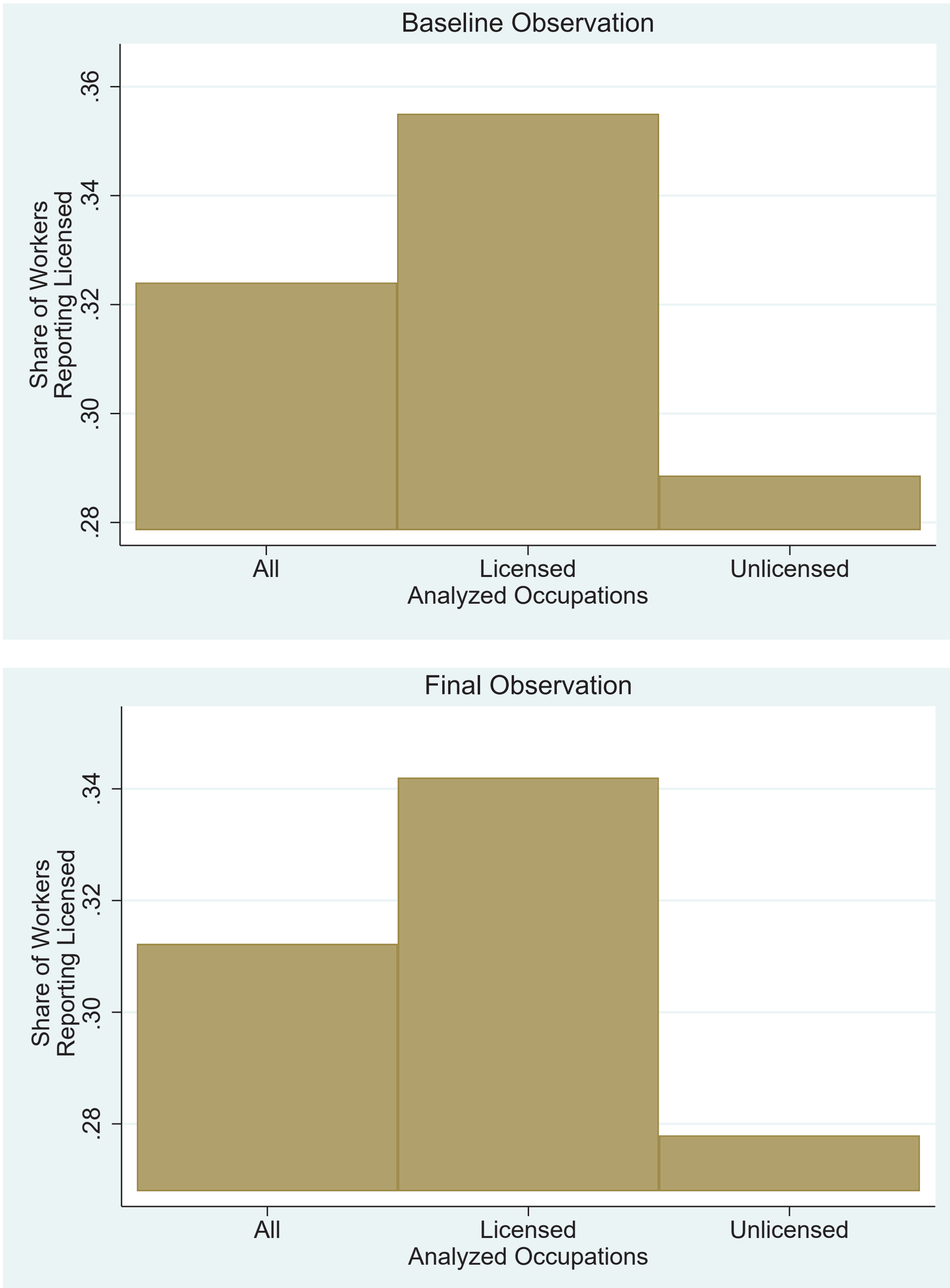
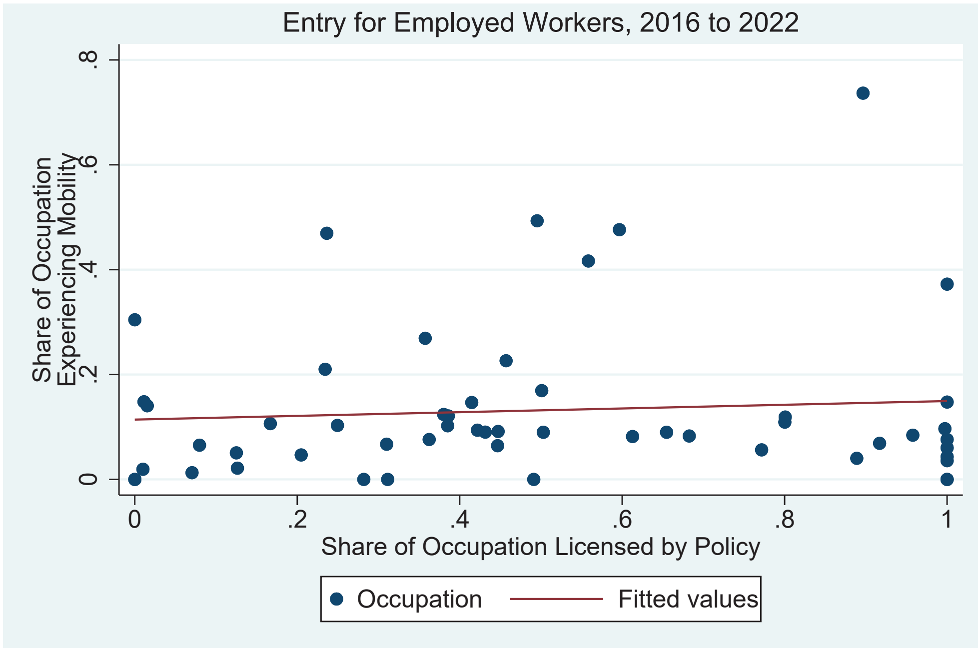


Figure 1: Licensing Variation: Self-Reported vs. Policy
Source(s): 2015–2022 Current Population Survey data, Carpenter II et al. (2017) and Knepper et al. (2022) data, and author's calculations.



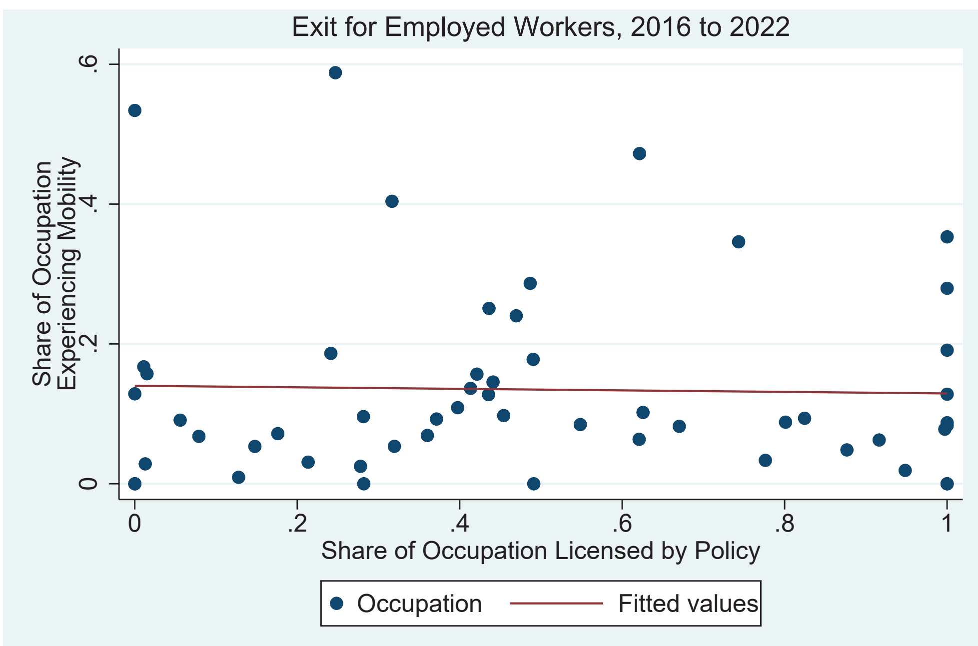
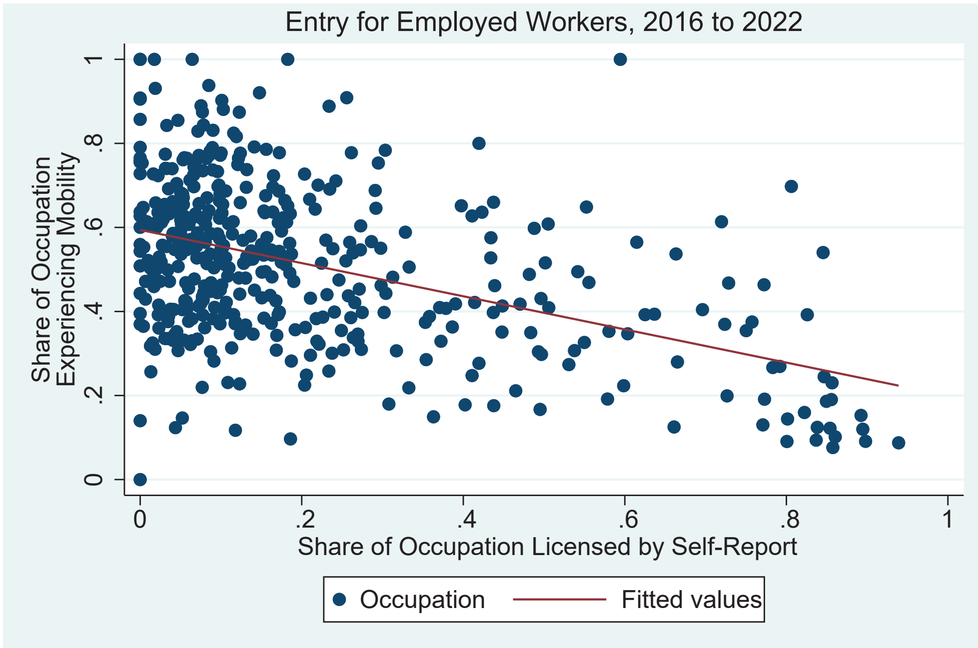


Figure 2: Licensing and Occupational Mobility, Correlation: Analyzed Occupations, Policy Licensing, Analyzed Mobility

Source(s): 2015–2022 Current Population Survey data, Carpenter II et al. (2017) and Knepper et al. (2022) data, and author's calculations.



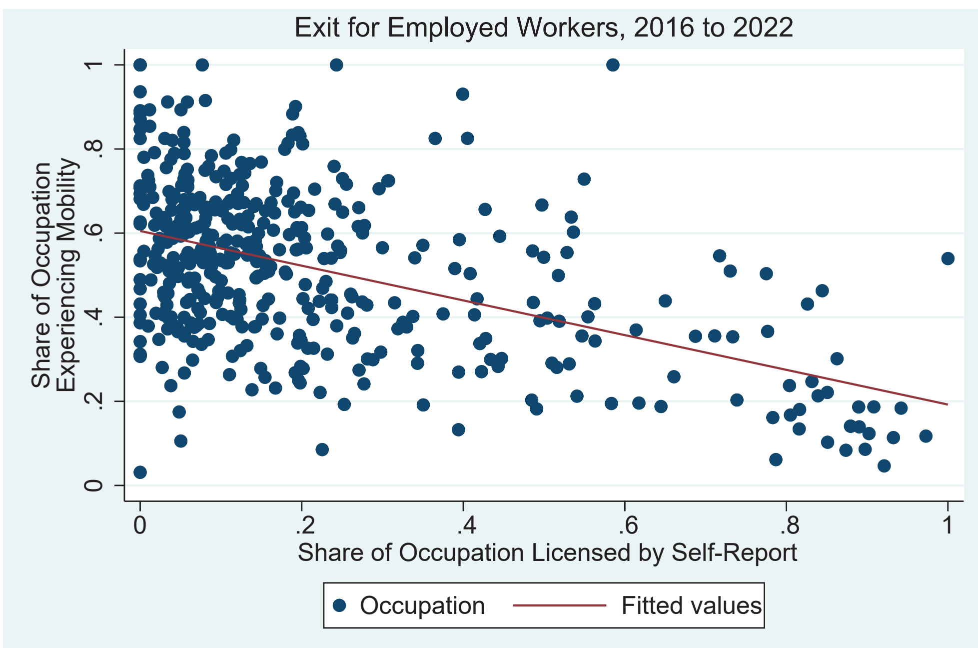


Figure 3: Licensing and Occupational Mobility, Correlation: All Occupations, Self-Reported Licensing, All Mobility

Source(s): 2015–2022 Current Population Survey data and author's calculations.

Table 1: Analyzed Occupations

Occupation name	CPS code	Occupation name	CPS code
Animal Control Officer	3900	Insulation Contractor (Commercial)	6400
Animal Trainer	4340	Interpreter, Sign Language	2860
Barber	4500	Iron/Steel Contractor (Commercial)	6530
Bartender	4040	Locksmith	7540
Bill Collection Agency	5100	Log Scaler	6130
Carpenter/Cabinet Maker Contractor (Commercial)	6230	Mason Contractor (Commercial)	6220
Child Care Home, Family	4600	Massage Therapist	3630
Coach, Head (High School Sports)	2720	Milk Sampler	5630
Conveyor Operator	9560	Optician	3520
Cosmetologist	4510	Painting Contractor (Commercial)	6420
Crane Operator	9510	Paving Contractor (Commercial)	6320
Dental Assistant	3640	Pest Control Applicator	4240
Door Repair Contractor (Commercial)	7300	Pipelayer Contractor	6440
Drywall Installation Contractor (Commercial)	6330	Preschool Teacher, Public School	2300
Earth Driller, Water Well	6820	Psychiatric Aide	3600
Emergency Medical Technician	3400	Security Alarm Installer	7130
Farm Labor Contractor	0620	Security Guard, Unarmed	3930
Fisher, Commercial	6100	Sheet Metal Contractor, HVAC (Commercial)	6520
Floor Sander Contractor (Commercial)	6240	Slot Supervisor	4320
Forest Worker	6120	Still Machine Setter, Dairy Equipment	8640
Funeral Attendant	4460	Taxi Driver/Chauffeur	9140
Gaming Cage Worker	5165	Teacher Assistant, Non-Instructional	2540
Gaming Dealer	4400	Title Examiner	2150
Gaming Supervisor	0430	Travel Agency	4830
Glazier Contractor (Commercial)	6360	Travel Guide	4540
Home Entertainment Installer	7120	Upholsterer	8450
HVAC Contractor (Commercial)	7315	Weigher	8740

Source(s) : 2015–2022 Current Population Survey data, Carpenter II et al. (2017) and Knepper et al. (2022) data, and author's calculations.
Note(s) : Occupation names (54 in total) reflect job titles in Carpenter II et al. (2017) and Knepper et al. (2022), while CPS codes reflect OCC2010 values in Flood et al. (2022).

Table 2: Worker Characteristics, 2015–2022

	At Baseline			*At Final*		
Indicator Measure	**Analyzed**	**Unanalyzed**	**Analyzed - Unanalyzed**	**Analyzed**	**Unanalyzed**	**Analyzed - Unanalyzed**
Reported being licensed	0.320	0.250	0.070***	0.310	0.241	0.070***
Female	0.447	0.458	-0.011**	0.447	0.458	-0.011**
Married	0.633	0.632	0.001	0.641	0.643	-0.002
Any children	0.512	0.480	0.032***	0.513	0.483	0.030***
Any children < age 5	0.132	0.128	0.004	0.119	0.119	0.000
Age						
16-34	0.234	0.259	-0.025***	0.209	0.235	-0.026***
35-54	0.496	0.475	0.021***	0.491	0.472	0.018***
55+	0.270	0.265	0.004	0.300	0.292	0.008
Education						
Less than high school	0.078	0.061	0.017***	0.068	0.053	0.015***
High school graduate	0.315	0.241	0.075***	0.310	0.236	0.074***
Some college	0.322	0.265	0.057***	0.332	0.268	0.064***
Bachelor's degree or more	0.285	0.433	-0.148***	0.290	0.443	-0.153***
Period						
2015–2018 (baseline)/2016–2019 (final)	0.612	0.616	-0.004	0.575	0.577	-0.002
2019–2021 (baseline)/2020–2022 (final)	0.388	0.384	0.004	0.425	0.423	0.002
Race/ethnicity						
White non-hispanic	0.677	0.705	-0.028***	0.677	0.705	-0.028***
Black non-hispanic	0.102	0.081	0.021***	0.102	0.081	0.021***
Asian non-hispanic	0.045	0.061	-0.015***	0.045	0.061	-0.015***
Other non-hispanic	0.017	0.018	-0.001	0.017	0.018	-0.001
Hispanic	0.159	0.135	0.024***	0.159	0.135	0.024***
Region						
New England	0.056	0.052	0.004**	0.056	0.052	0.004**
Middle Atlantic	0.128	0.118	0.010**	0.128	0.118	0.010**
East North Central	0.156	0.163	-0.007*	0.156	0.163	-0.007*
West North Central	0.085	0.083	0.002	0.085	0.083	0.002
South Atlantic	0.187	0.187	0.000	0.187	0.187	0.000
East South Central	0.053	0.059	-0.006***	0.053	0.059	-0.006***
West South Central	0.110	0.110	0.000	0.110	0.110	0.000
Mountain	0.074	0.073	0.001	0.074	0.073	0.001
Pacific	0.151	0.155	-0.004	0.151	0.155	-0.004
Industry						
Agriculture, forestry, and fishing	0.004	0.025	-0.021***	0.004	0.025	-0.021***
Mining	0.004	0.005	-0.001	0.004	0.006	-0.001
Construction	0.240	0.053	0.187***	0.242	0.054	0.188***
Manufacturing	0.093	0.121	-0.028***	0.093	0.121	-0.028***
Transportation, communication, and other utilities	0.059	0.072	-0.013***	0.059	0.074	-0.016***
Wholesale and retail trade	0.034	0.179	-0.145***	0.035	0.173	-0.138***
Finance, insurance, and real estate	0.021	0.079	-0.058***	0.020	0.080	-0.059***
Various services	0.504	0.411	0.094***	0.503	0.412	0.091***
Public administration	0.039	0.054	-0.015***	0.040	0.055	-0.016***
Occupation						
Management in business, science, and arts	0.226	0.135	0.092***	0.227	0.138	0.089***
Business operations specialists	0.047	0.029	0.018***	0.047	0.029	0.019***
Financial specialists	0.000	0.030	-0.030***	0.000	0.030	-0.030***
Computer and mathematical	0.000	0.043	-0.043***	0.000	0.042	-0.042***
Architecture and engineering	0.000	0.025	-0.025***	0.000	0.025	-0.025***
Technicians	0.000	0.004	-0.004***	0.000	0.004	-0.004***
Life, physical, and social science	0.000	0.012	-0.012***	0.000	0.012	-0.012***
Community and social services	0.000	0.019	-0.019***	0.000	0.019	-0.019***
Legal	0.002	0.016	-0.014***	0.002	0.016	-0.015***
Education, training, and library	0.097	0.061	0.036***	0.097	0.060	0.037***
Arts, design, entertainment, sports, and media	0.017	0.019	-0.002	0.017	0.019	-0.002
Healthcare practitioners and technicians	0.013	0.071	-0.059***	0.012	0.072	-0.059***
Healthcare support	0.113	0.011	0.102***	0.112	0.011	0.101***
Protective service	0.042	0.017	0.025***	0.043	0.017	0.026***
Food preparation and serving	0.014	0.037	-0.023***	0.014	0.034	-0.019***
Building and grounds cleaning and maintenance	0.000	0.034	-0.034***	0.000	0.034	-0.034***
Personal care and service	0.116	0.021	0.095***	0.115	0.020	0.094***
Sales and related	0.001	0.102	-0.100***	0.001	0.101	-0.100***
Office and administrative support	0.001	0.122	-0.121***	0.001	0.123	-0.122***
Farming, fisheries, and forestry	0.004	0.006	-0.002***	0.004	0.006	-0.002***
Construction	0.205	0.033	0.172***	0.203	0.033	0.170***
Extraction	0.000	0.001	-0.001***	0.000	0.001	-0.001***
Installation, maintenance, and repair	0.034	0.035	-0.001	0.035	0.035	0.000
Production	0.040	0.059	-0.019***	0.040	0.058	-0.018***
Transportation and material moving	0.028	0.058	-0.031***	0.028	0.059	-0.031***
Number of workers	12,004	145,100		12,004	145,100	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source(s) : 2015–2022 Current Population Survey data and author's calculations.

Note(s) : Statistics for analyzed and unanlyzed workers use unadjusted CPS weights. Occupation names reflect groupings of CPS OCC2010 designations in Flood et al (2022).

Table 3: Impact of Extensive-Margin Licensing on Occupational Mobility (Entry)

	Dependent Variable: Occupation Change in 15 Months (0/1)						
	Unweighted	Weighted					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Licensed	0.003	0.003	0.005	0.002	-0.019***	-0.023***	-0.022***
	(0.005)	(0.006)	(0.006)	(0.006)	(0.008)	(0.008)	(0.008)
Controls	no	no	yes	no	no	no	yes
State	no	no	no	yes	no	yes	yes
Occupation	no	no	no	no	yes	yes	yes
Unlicensed Mean of Outcome	0.092	0.092	0.092	0.092	0.092	0.092	0.092
R-squared	0.000	0.000	0.019	0.004	0.054	0.058	0.074
Number of Observations	12,003	12,003	12,003	12,003	12,003	12,003	12,003
Number of LIcensed Workers	6,226	6,226	6,226	6,226	6,226	6,226	6,226
Number of Unlicensed Workers	5,777	5,777	5,777	5,777	5,777	5,777	5,777

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source(s) : 2015–2022 Current Population Survey data, Carpenter II et al. (2017) and Knepper et al. (2022) data, and author's calculations.

Note(s) : The licensed indicator reflects state-occupation policy and is measured in the final month-in-sample. State indicators, occupation indicators, and other controls are also all measured in the final month-in-sample. Weights are CPS weights reflecting survey sample design and further adjusted for post-stratification sample selection. Heteroskedasticity-robust standard errors are in parentheses.

Table 4: Impact of Extensive-Margin Licensing on Occupational Mobility (Exit)

	Dependent Variable: Occupation Change in 15 Months (0/1)						
	Unweighted	Weighted					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Licensed	0.008	0.006	0.007	0.006	-0.009	-0.011	-0.012
	(0.005)	(0.006)	(0.006)	(0.006)	(0.007)	(0.008)	(0.008)
Controls	no	no	yes	no	no	no	yes
State	no	no	no	yes	no	yes	yes
Occupation	no	no	no	no	yes	yes	yes
Unlicensed Mean of Outcome	0.089	0.089	0.089	0.089	0.089	0.089	0.089
R-squared	0.000	0.000	0.019	0.004	0.057	0.061	0.073
Number of Observations	12,002	12,002	12,002	12,002	12,002	12,002	12,002
Number of LIcensed Workers	6,228	6,228	6,228	6,228	6,228	6,228	6,228
Number of Unlicensed Workers	5,774	5,774	5,774	5,774	5,774	5,774	5,774

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source(s) : 2015–2022 Current Population Survey data, Carpenter II et al. (2017) and Knepper et al. (2022) data, and author's calculations.

Note(s) : The licensed indicator reflects state-occupation policy and is measured in the baseline month-in-sample. State indicators, occupation indicators, and other controls are also all measured in the baseline month-in-sample. Weights are CPS weights reflecting survey sample design and further adjusted for post-stratification sample selection. Heteroskedasticity-robust standard errors are in parentheses.

Table 5: Robustness of Impact of Extensive-Margin Licensing on Occupational Mobility (Entry)

	Dependent Variable: Occupation Change in 15 Months (0/1)									Dep Var: Self-Report Licensed (0/1)
	8 MIS (1)	State-Occupation (2)	Region-Occupation (3)	State-Occupation Group (4)	Baseline Occupation (5)	All Mobility (6)	More Commonly Licensed (7)	Less Commonly Licensed (8)	Self-Report Licensed (9)	First Stage IV (10)
Licensed	-0.019**	0.039	-0.025**	-0.045***	-0.021***	-0.019*	-0.014	-0.044***	0.014**	0.014
	(0.009)	(0.051)	(0.010)	(0.015)	(0.008)	(0.011)	(0.012)	(0.012)	(0.007)	(0.011)
F-Statistic (Licensed = 0)										1.563
R-squared	0.081	0.170	0.108	0.096	0.125	0.115	0.090	0.060	0.074	0.249
Number of Observations	10,853	11,605	11,957	12,001	12,002	20,101	7,554	4,449	12,003	12,003
Number of Licensed Workers	5,688	6,031	6,206	6,226	6,225	10,380	5,212	1,014	3,821	6,226
Number of Unlicensed Workers	5,165	5,574	5,751	5,775	5,777	9,720	2,342	3,435	8,182	5,777

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source(s) : 2015–2022 Current Population Survey data, Carpenter II et al. (2017) and Knepper et al. (2022) data, and author's calculations.

Note(s) : The licensed indicator reflects state-occupation policy and is measured in the final month-in-sample. Unless otherwise indicated, all models include state indicators, occupation indicators, and other controls, all measured in the final month-in-sample. Column (1) restricts the sample to workers surveyed for all eight months-in-sample. Column (2) replaces state and occupation indicators with state x occupation indicators. Column (3) replaces occupation indicators with region x occupation indicators, where regions reflect nine census divisions: (i) New England; (ii) Middle Atlantic; (iii) East North Central; (iv) West North Central; (v) South Atlantic; (vi) East South Central; (vii) West South Central; (viii) Mountain; and (ix) Pacific. Column (4) replaces state indicators with state x occupation group indicators, where occupation groups reflect eight broad categories outlined by Knepper et al. (2022): (i) animals, agriculture, and outdoors; (ii) construction and home services; (iii) education; (iv) entertainment and hospitality; (v) health; (vI) other; (vii) personal care services; and (viii) transportation and machinery. Column (5) adds occupation indicators measured in the baseline month-in-sample. Column (6) enlarges the sample to allow the dependent variable to reflect potential occupational switching from any occupation in the baseline month-in-sample to any analyzed occupation in the final month-in-sample. Columns (7) and (8) stratify the sample based on which occupations are more commonly licensed (licensed in a count of states at or above the median count of licensed states for analyzed occupations) and which occupations are less commonly licensed (licensed in a count of states below the median count of licensed states for analyzed occupations). Column (9) replaces the indicator for licensed state-occupation policy in the final month-in-sample and instead uses an indicator for a worker's self-reported licensing status. Column (10) reflects a first stage instrumental variables specification with self-reported licensed status in the final month-in-sample as the dependent variable. All specifications are weighted, where weights are CPS weights reflecting survey sample design and further adjusted for post-stratification sample selection. Heteroskedasticity-robust standard errors are in parentheses.

Table 6: Impact of Intensive-Margin Licensing on Occupational Mobility (Entry)

	Dependent Variable: Occupation Change in 15 Months (0/1)				
	Licensed	Fees	Exams	Minimum Grade	Minimum Age
	(1)	(2)	(3)	(4)	(5)
Licensing measure	-0.022***	-0.018*	-0.003	-0.002*	-0.001*
	(0.008)	(0.010)	(0.006)	(0.001)	(0.000)
R-squared	0.074	0.074	0.073	0.074	0.074
Number of Observations	12,003	12,003	12,003	12,003	12,003
Number of Licensed Workers	6,226	6,226	6,226	6,226	6,226
Number of Unlicensed Workers	5,777	5,777	5,777	5,777	5,777

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source(s) : 2015–2022 Current Population Survey data, Carpenter II et al. (2017) and Knepper et al. (2022) data, and author's calculations.

Note(s) : The licensing measures reflect state-occupation policy and are measured in the final month-in-sample. All models include state indicators, occupation indicators, and other controls, all measured in the final month-in-sample. Column (1) reposts the extensive-margin licensing effect obtained with a licensed indicator reflecting state-occupation policy. Columns (2) through (5) display intensive-margin licensing effects using continous measures of licensing fees (in constant 1999 thousands of US dollars), licensing exams, and minimum thresholds for a licensed worker's school grade attained and age. All specifications are weighted, where weights are CPS weights reflecting survey sample design and further adjusted for post-stratification sample selection. Heteroskedasticity-robust standard errors are in parentheses.

Table 7: Impact of Intensive-Margin Licensing on Occupational Mobility, Stratified (Entry)

	Dependent Variable: Occupation Change in 15 Months (0/1)					
	Fees		Minimum Grade		Minimum Age	
	Below Median	At or Above Median	Below Median	At or Above Median	Below Median	At or Above Median
	(1)	(2)	(3)	(4)	(5)	(6)
Licensed	-0.011	-0.026**	-0.032	-0.020	-0.005	-0.016*
	(0.010)	(0.011)	(0.028)	(0.013)	(0.028)	(0.008)
R-squared	0.080	0.083	0.076	0.075	0.072	0.078
Number of Observations	9,033	9,171	11,332	11,679	8,647	11,406
Number of Treatment Workers	2,830	2,967	324	671	597	3,355
Number of Control Workers	6,203	6,204	11,008	11,008	8,050	8,051

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source(s) : 2015–2022 Current Population Survey data, Carpenter II et al. (2017) and Knepper et al. (2022) data, and author's calculations.

Note(s) : The licensed indicator reflects state-occupation policy and is measured in the final month-in-sample. All models include state indicators, occupation indicators, and other controls, all measured in the final month-in-sample. Strata allocate treatment-group workers (licensed workers in a state-occupation that imposes the applicable intensive-margin licensing qualification) based on quantiles of positive intensive-margin licensing measure values at the state-occupation-period level, where a period reflects timing in the final month-in-sample and is either 2016–2019 or 2020–2022. For a given intensive-margin licensing measure, control-group workers (unlicensed workers in a state-occupation or licensed workers in a state-occupation that does not impose the applicable intensive-margin licensing qualification) reflect intensive-margin licensing measure values of 0 and are approximately constant across strata. All specifications are weighted, where weights are CPS weights reflecting survey sample design and further adjusted for post-stratification sample selection. Heteroskedasticity-robust standard errors are in parentheses.

Table 8: Characterizing Impact of High Intensive-Margin Licensing on Occupational Mobility by Various Forms of Heterogeneity (Entry)

	Dependent Variable: Occupation Change in 15 Months (0/1)		
	Fees: At or Above Median	Min. Grade: At or Above Median	Min. Age: At or Above Median
Licensed	(1)	(2)	(3)
Occupational Group			
Other		-0.563***	
		(0.174)	
Industry			
Construction	-0.077**		
	(0.031)		
Finance, Insurance, and Real Estate	0.157*		
	(0.095)		
Various Services		-0.067***	-0.032*
		(0.022)	(0.017)
Public Administration		-0.247*	
		(0.136)	
Region			
New England	-0.106*		-0.069*
	(0.055)		(0.037)
Middle Atlantic	-0.086**		
	(0.039)		
West South Central	-0.085*		
	(0.048)		
Pacific	-0.103**		-0.127***
	(0.052)		(0.046)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source(s) : 2015–2022 Current Population Survey data, Carpenter II et al. (2017) and Knepper et al. (2022) data, and author's calculations.

Note(s) : Each cell displays the coefficient of the licensed indicator from a separate regression corresponding to the sample indicated. The licensed indicator reflects state-occupation policy and is measured in the final month-in-sample. All models include state indicators, occupation indicators, and other controls, all measured in the final month-in-sample. All specifications are weighted, where weights are CPS weights reflecting survey sample design and further adjusted for post-stratification sample selection. Heteroskedasticity-robust standard errors are in parentheses.

A Appendix

A.1 Descriptive Weight Construction

As noted in the main text and similar to the approach in Jackson (2021), given numerous sample restrictions for the data, I create a descriptive weight for all workers to reflect their nationally representative count. These weights incorporate both a "sample design" component and a "post-stratification" component. The two components are multiplied to generate the descriptive weight, $WTALL$, which is used for both descriptive and causal analysis, as noted in the main text and displays.

For the sample design weight component, I adjust the $WTFINL$ measure provided by IPUMS-CPS. $WTFINL$ is described as "the final person-level weight that should be used in analyses of basic monthly data" and "is based on the inverse probability of selection into the sample" with additional adjustments for various factors (Flood et al. 2022). I use the MIS1 value of $WTFINL$ for each worker.

For the post-stratification weight component, the goal is to further adjust the descriptive weight for any differential sample selection across a set of key individual traits. Such selection is determined by comparing the baseline sample of individuals with person-level IDs noted in Appendix Table A1 (call this the "raw" sample) and the prospective analysis sample noted in Appendix Table A2 (call this the "final" sample, although unemployed workers are ultimately omitted from analysis due to small sample counts). Once again, I focus on the MIS1 value for each individual trait. Both the raw and final samples reflect the resulting 2015–2021 calendar years spanned by workers in MIS1, and both samples are also restricted to persons age 16 and older since the analysis sample is constrained to such individuals. I focus on five categories for individual traits, with the corresponding number of values for each measure indicated in parentheses: sex (2), age (2), education (3), period (2), and area (9).[14] Every person is uniquely assigned to one bin among all 216 possible bin combinations from those five traits. For each bin and the corresponding workers assigned to those bins, the post-stratification weight, $WTPOST$, is the count of persons in the raw sample divided by the count of persons in the final sample.

The final descriptive weight for each worker in the analysis sample, $WTALL$, is thus $WTFINL \times WTPOST$. As noted in the main text, I run validity checks to compare various population statistics (shares) with those generated by the analysis sample with the $WTALL$ descriptive weight applied. In these validity checks, I am able to closely replicate the chosen population statistics.

[14] Regarding category values: sex is male or female; age is 16 through 44 or 45 and older; education is high school (diploma or equivalent, including persons "not in universe" or with missing responses) or less, some college (including associate degree), and college (bachelor's degree) or more; period is 2015 through 2018 or 2019 through 2021; and area (region) is New England, Middle Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain, and Pacific, reflecting census divisions and the associated states (Flood et al. 2022).

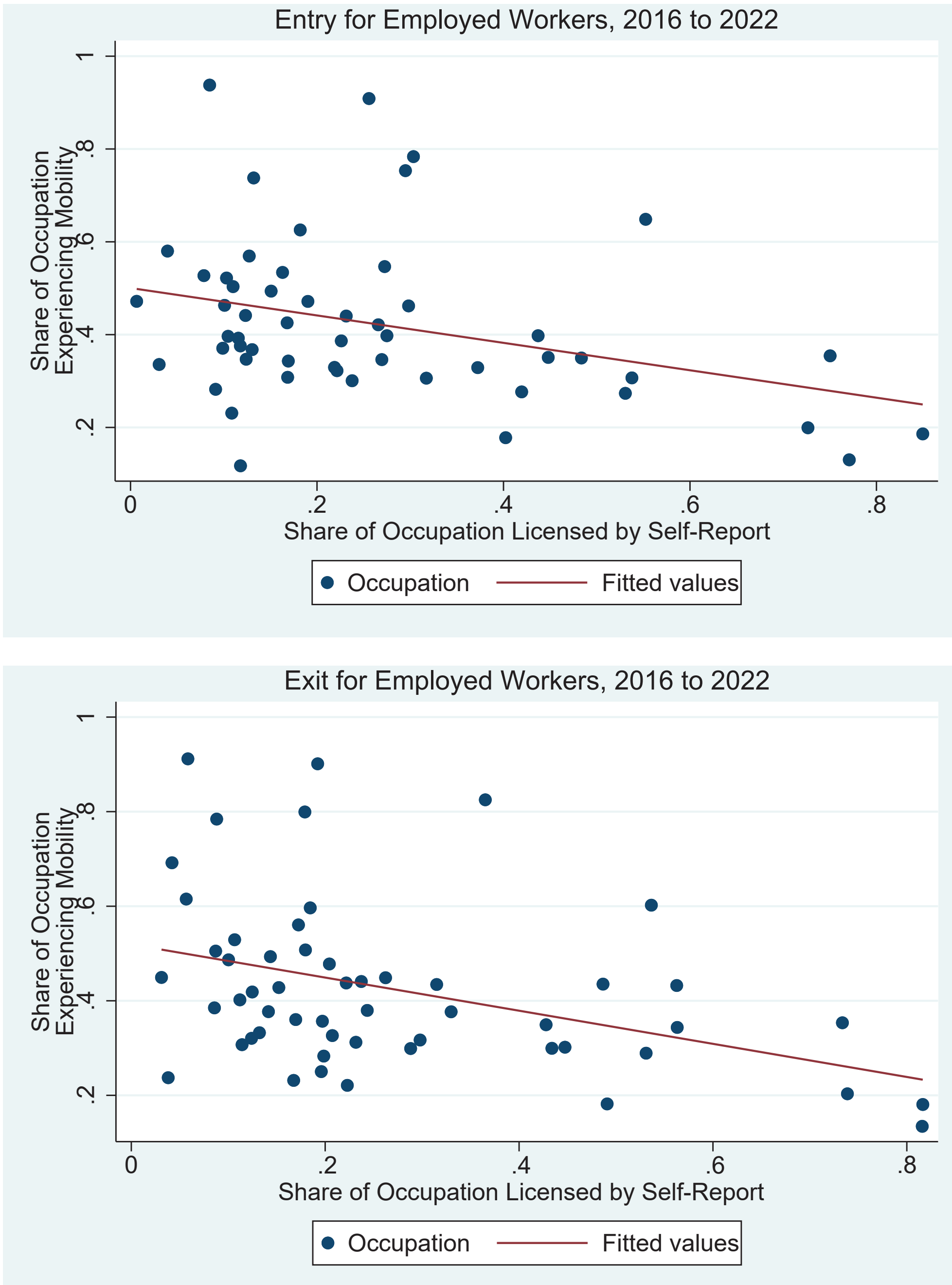
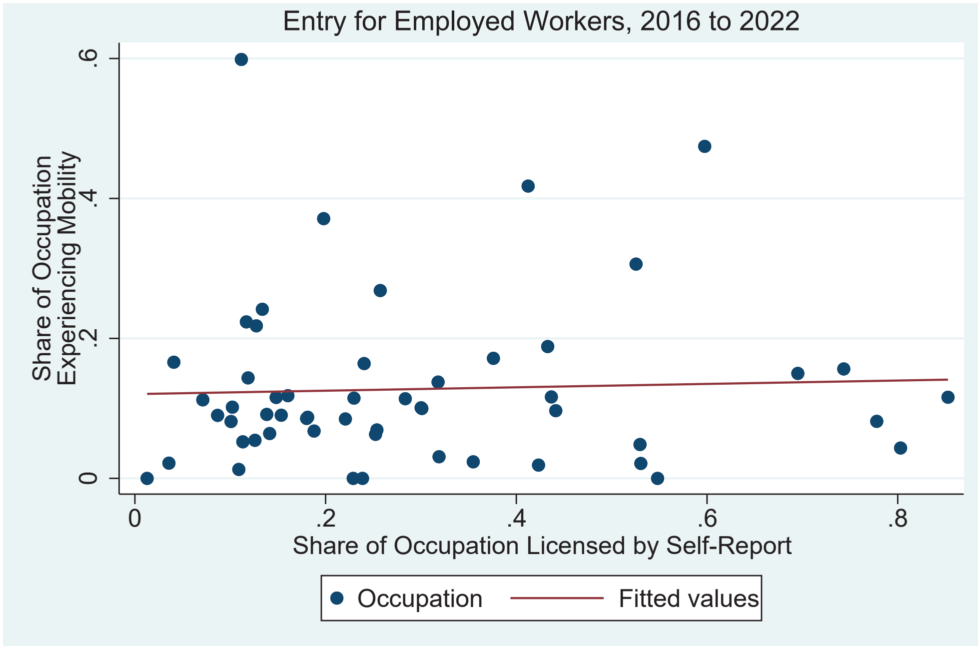


Figure A1: Licensing and Occupational Mobility, Correlation: Analyzed Occupations, Self-Reported Licensing, All Mobility

Source(s): 2015–2022 Current Population Survey data, Carpenter II et al. (2017) and Knepper et al. (2022) data, and author's calculations.



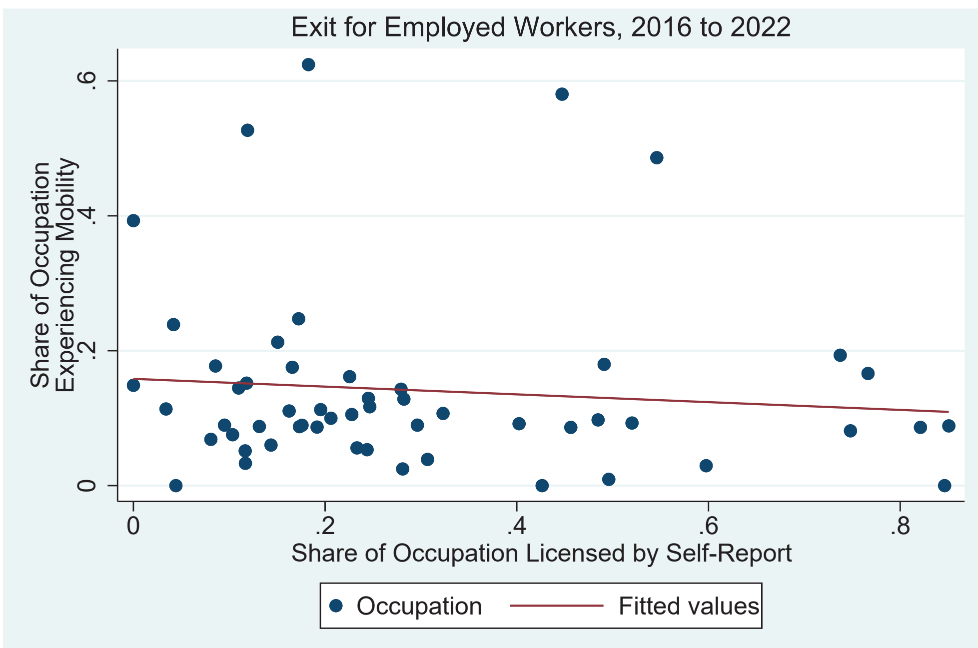


Figure A2: Licensing and Occupational Mobility, Correlation: Analyzed Occupations, Self-Reported Licensing, Analyzed Mobility

Source(s): 2015–2022 Current Population Survey data, Carpenter II et al. (2017) and Knepper et al. (2022) data, and author's calculations.

Table A1: Initial Sample Selection

Sample Restriction	Count			Percentage of Baseline		
	Household	Individual	Observation	Household	Individual	Observation
Baseline w/ CPSIDP (person ID)	883,774	2,210,620	11,533,325	100.00	100.00	100.00
Drop if CPSIDP only appears once	821,025	2,033,393	11,356,098	92.90	91.98	98.46
Drop if under age 16	820,993	1,609,799	9,052,763	92.90	72.82	78.49
Drop if not in BMS for at least 2 months-in-sample	342,744	636,019	4,972,175	38.78	28.77	43.11
Drop if race varies across time	338,756	628,683	4,922,336	38.33	28.44	42.68
Drop if Hispanic varies across time	337,227	625,440	4,899,988	38.16	28.29	42.49
Drop if sex varies across time	333,980	619,262	4,859,250	37.79	28.01	42.13
Drop if age varies incorrectly across time	274,218	444,327	3,494,985	31.03	20.10	30.30
Drop if industry unknown or military or NIU	173,091	235,861	1,853,315	19.59	10.67	16.07
Drop if occupation unknown/NIU or military	173,091	235,861	1,853,315	19.59	10.67	16.07
Drop if state unavailable for any month-in-sample	173,091	235,861	1,853,315	19.59	10.67	16.07
Drop if state varies across time	173,091	235,861	1,853,315	19.59	10.67	16.07
Drop if MIS1 is before January 2015	173,091	235,861	1,853,315	19.59	10.67	16.07
Drop if MIS2 is in June 2015	170,737	232,690	1,828,280	19.32	10.53	15.85
Drop if same-employer measure is unexplainably NIU	148,561	199,997	1,575,147	16.81	9.05	13.66
Drop if same-employer measure is unexplainably IU	148,328	199,582	1,572,215	16.78	9.03	13.63
Drop if industry changes without employer change	146,678	196,809	1,550,413	16.60	8.90	13.44
Drop if working multiple jobs in any MIS	131,975	170,857	1,345,759	14.93	7.73	11.67
Drop if employment status is military or NIU	131,975	170,857	1,345,759	14.93	7.73	11.67
Drop if same-employer measure is refused or unknown	131,903	170,753	1,344,980	14.92	7.72	11.66
Drop if same-work measure is unexplainably NIU	130,255	168,162	1,324,742	14.74	7.61	11.49
Drop if same-work measure is unexplainably IU	130,255	168,162	1,324,742	14.74	7.61	11.49
Drop if same-work measure is refused or unknown	130,139	168,005	1,323,506	14.73	7.60	11.48
Drop if certification/license measure is unexplainably NIU	130,139	168,005	1,323,506	14.73	7.60	11.48
Drop if certification/license measure is unexplainably IU	130,139	168,005	1,323,506	14.73	7.60	11.48
Drop if govt. certification/license measure is unexplainably NIU	130,139	168,005	1,323,506	14.73	7.60	11.48
Drop if govt. certification/license measure is unexplainably IU	130,139	168,005	1,323,506	14.73	7.60	11.48

Source(s) : 2015–2022 Current Population Survey data and author's calculations.
Note(s) : NIU is not in universe, and IU is in universe.

Table A2: Additional Sample Selection

Subsample A: Workers Employed in First Month-in-Sample

Sample Restriction	Count			Percentage of Baseline		
	Household	Individual	Observation	Household	Individual	Observation
Baseline w/ initial restrictions	130,139	168,005	1,323,506	100.00	100.00	100.00
Drop if not employed in MIS1	127,929	164,415	1,295,365	98.30	97.86	97.87
Drop if not MIS1 or MIS8	127,929	164,415	328,830	98.30	97.86	24.85
Drop if not linked to policy data	14,956	15,462	30,924	11.49	9.20	2.34
Drop if occupation does not meet criteria	13,458	13,904	27,808	10.34	8.28	2.10
Drop if not self-employed in owner occupations	12,300	12,674	25,348	9.45	7.54	1.92
Drop if MIS8 is in 2023	12,049	12,414	24,828	9.26	7.39	1.88

Subsample B: Workers Unemployed in First Month-in-Sample

Sample Restriction	Count			Percentage of Baseline		
	Household	Individual	Observation	Household	Individual	Observation
Baseline w/ initial restrictions	130,139	168,005	1,323,506	100.00	100.00	100.00
Drop if not unemployed in MIS1	3,513	3,590	28,141	2.70	2.14	2.13
Drop if not MIS1 or MIS8	3,513	3,590	7,180	2.70	2.14	0.54
Drop if not linked to policy data	336	337	674	0.26	0.20	0.05
Drop if occupation does not meet criteria	310	311	622	0.24	0.19	0.05
Drop if not self-employed in owner occupations	277	278	556	0.21	0.17	0.04
Drop if MIS8 is in 2023	276	277	554	0.21	0.16	0.04

Source(s) : 2015–2022 Current Population Survey data, Carpenter II et al. (2017) and Knepper et al. (2022) data, and author's calculations.
Note(s) : NIU is not in universe.

Table A3: Worker Characteristics in Licensed and Unlicensed State-Occupations, 2015–2022

	At Baseline			*At Final*		
Indicator Measure	**Licensed**	**Unlicensed**	**Licensed - Unlicensed**	**Licensed**	**Unlicensed**	**Licensed - Unlicensed**
Reported being licensed	0.355	0.289	0.066***	0.342	0.278	0.064***
Female	0.490	0.535	-0.045***	0.491	0.534	-0.043***
Married	0.650	0.611	0.039***	0.652	0.623	0.029***
Any children	0.515	0.512	0.004	0.516	0.513	0.002
Any children < age 5	0.136	0.124	0.012	0.123	0.109	0.014**
Age						
35-54	0.512	0.487	0.025**	0.508	0.480	0.028***
55+	0.260	0.279	-0.019**	0.289	0.312	-0.023**
Education						
High school graduate	0.307	0.367	-0.060***	0.292	0.354	-0.063***
Some college	0.267	0.269	-0.002	0.288	0.290	-0.002
Bachelor's degree or more	0.358	0.281	0.076***	0.361	0.281	0.080***
Period						
2019–2021 [baseline]/2020–2022 [final]	0.418	0.411	0.008	0.457	0.443	0.014
Race/ethnicity						
Black non-hispanic	0.089	0.134	-0.045***	0.088	0.135	-0.047***
Asian non-hispanic	0.061	0.037	0.024***	0.061	0.037	0.024***
Other non-hispanic	0.020	0.015	0.005*	0.020	0.014	0.007**
Hispanic	0.162	0.160	0.003	0.161	0.160	0.001
Region						
Middle Atlantic	0.113	0.134	-0.021***	0.114	0.134	-0.020***
East North Central	0.121	0.169	-0.048***	0.122	0.169	-0.047***
West North Central	0.052	0.086	-0.034***	0.051	0.088	-0.037***
South Atlantic	0.207	0.193	0.015	0.213	0.186	0.027***
East South Central	0.055	0.062	-0.007	0.055	0.063	-0.008
West South Central	0.089	0.158	-0.069***	0.088	0.159	-0.071***
Mountain	0.083	0.066	0.017***	0.084	0.066	0.017***
Pacific	0.231	0.084	0.147***	0.227	0.088	0.139***
Industry						
Mining	0.003	0.006	-0.003**	0.003	0.006	-0.004**
Construction	0.194	0.216	-0.022***	0.194	0.221	-0.027***
Manufacturing	0.107	0.075	0.032***	0.106	0.076	0.030***
Transportation, communication, and other utilities	0.056	0.060	-0.004	0.055	0.059	-0.004
Wholesale and retail trade	0.029	0.038	-0.009**	0.030	0.039	-0.009**
Finance, insurance, and real estate	0.023	0.021	0.002	0.023	0.020	0.002
Various services	0.539	0.541	-0.001	0.540	0.536	0.004
Public administration	0.045	0.038	0.007*	0.045	0.037	0.008*
Occupation						
Business operations specialists	0.034	0.070	-0.035***	0.035	0.070	-0.035***
Legal	0.000	0.004	-0.004***	0.000	0.004	-0.004***
Education, training, and library	0.089	0.129	-0.040***	0.091	0.129	-0.038***
Arts, design, entertainment, sports, and media	0.024	0.011	0.013***	0.024	0.011	0.013***
Healthcare practitioners and technicians	0.020	0.003	0.017***	0.019	0.003	0.016***
Healthcare support	0.026	0.241	-0.216***	0.025	0.242	-0.217***
Protective service	0.057	0.020	0.037***	0.058	0.021	0.038***
Food preparation and serving	0.005	0.023	-0.017***	0.005	0.024	-0.018***
Building and grounds cleaning and maintenance	0.001	0.000	0.001**	0.000	0.000	0.000**
Personal care and service	0.206	0.031	0.175***	0.203	0.032	0.172***
Sales and related	0.001	0.002	0.000	0.001	0.001	-0.001
Office and administrative support	0.001	0.002	-0.001	0.001	0.002	0.000
Farming, fisheries, and forestry	0.002	0.005	-0.003***	0.002	0.005	-0.003***
Construction	0.143	0.209	-0.066***	0.139	0.210	-0.071***
Extraction	0.000	0.000	0.000	0.000	0.000	0.000
Installation, maintenance, and repair	0.041	0.015	0.026***	0.043	0.014	0.028***
Production	0.044	0.035	0.009**	0.044	0.037	0.007*
Transportation and material moving	0.014	0.036	-0.022***	0.014	0.037	-0.024***
Number of workers	6,230	5,774		6,227	5,777	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source(s) : 2015–2022 Current Population Survey data and author's calculations.

Note(s) : All statistics use CPS weights reflecting survey sample design and further adjusted for post-stratification sample selection. Licensed workers (treatment group) reflect persons in state-occupations that are licensed, according to policy. Unlicensed workers (control group) reflect persons in state-occupations that are unlicensed, according to policy. Licensed and unlicensed workers jointly reflect the analyzed sample. Omitted categories are 16–34 (age); less than high school (education); 2015–2018 [baseline]/2016–2019 [final] (period); white non-Hispanic (race/ethnicity); New England (region); agriculture, forestry, and fishing (industry); and management in business, science, and arts (occupation).