The Spillover Effects of Labor Regulations on the Structure of Earnings and Employment: Evidence from Occupational Licensing

Samuel Dodini
Norwegian School of Economics
samuel.dodini@nhh.no

February 2022

Abstract

This paper measures the effects of labor regulations on the structure of earnings and employment in the context of occupational licensing. Using a state border match design, I estimate the labor market spillovers of licensing on other occupations with similar skills, which I classify using hierarchical clustering techniques on skills data from O*NET. I find evidence of negative earnings and employment spillovers, with the largest earnings effects concentrated among women, black, and foreign-born Hispanic workers. These effects lead to greater earnings inequality. The results are consistent with a monopsony model where licensing increases search costs and reduces workers' outside options.

JEL Codes: J21, J24, J31, J42, J62, D63

*I am grateful to Michael Lovenheim, Maria Fitzpatrick, Evan Riehl, Seth Sanders, Alexander Willén, Bertil Tungodden, and Kjell Salvanes for helpful comments. I am also thankful to participants at the Knee Center Occupational Licensing Conference and seminar participants at Cornell University and the Norwegian School of Economics for helpful comments and discussion.

1 Introduction

Since the 1930s, economists have theorized about the possible consequences of imperfect labor markets (Robinson, 1933). Much of the recent empirical literature has focused on how imperfections in unregulated labor markets may negatively affect worker wages and employment. Sources of these imperfections include search frictions and switching costs (Webber, 2016; Ransom, 2021) and the concentration of labor demand (Azar et al., 2020; Dodini et al., 2020). Each of these may contribute to earnings and employment that are inefficiently low relative to a competitive equilibrium. There has been far less focus on the effects of possible market imperfections created by occupation-specific regulations.[1] This paper focuses on how occupational regulations affect workers by considering a growing source of strict oversight in the labor market: occupational licensing.

Occupational licensing is state-sanctioned permission to work in a particular occupation. These regulations on who can work in an occupation are typically passed in pursuit of protecting the health, safety, and well-being of consumers. Across the United States and Europe, licensing has grown during the last fifty years from affecting approximately 5% of workers to over 20% (Cunningham, 2019; Koumenta et al., 2014; Koumenta and Pagliero, 2019). As licensing grows, it becomes increasingly important to understand how these regulations affect workers and the structure of employment and earnings, particularly if they contribute to new market imperfections.

The current literature suggests that occupational licensing regulations in the US, most of which differ across states, have significant effects on the labor markets of the individual occupations being licensed.[2] There is also some evidence of wage spillovers for occupations that perform similar functions in the same narrow industries.[3] However, except for studies that examine occupations that perform overlapping duties, the prior literature has not considered how licensing regulations in one occupation spill over to affect the labor market experience of workers in other occupations. In particular, it is important to consider these questions: for workers that would have entered a licensed occupation *but for* the requirements of the license, where do they go, what are their earnings and employment rates, and how does that affect the labor market generally? The answer can inform economists, workers, and policymakers about the important ways in which occupational regulations may exacerbate income inequality and reduce economic efficiency. The answer also informs the literature in labor economics about

[1] For example, non-compete agreements (Starr et al., 2021; Lipsitz and Starr, 2022; Balasubramanian et al., 2020).

[2] Licenses reduce overall labor supply into licensed occupations (Blair and Chung, 2019; Kleiner and Soltas, 2019), change the composition of workers (Bailey and Belfield, 2018; Blair and Chung, 2018; Redbird, 2017), increase prices for goods and services produced by licensed workers (Adams III et al., 2002; Wing and Marier, 2014), generate a wage premium in licensed occupations (Kleiner and Krueger, 2013; Gittleman et al., 2018; Kleiner and Vorotnikov, 2017; Kleiner and Soltas, 2019; Pizzola and Tabarrok, 2017; Thornton and Timmons, 2013), and reduce interstate labor migration and occupational mobility (see Johnson and Kleiner (2017); Kugler and Sauer (2005) and Kleiner and Xu (2020)).

[3] See Cai and Kleiner (2016); Kleiner and Park (2010); Kleiner et al. (2016).

how specific public policies contribute to labor market power.

This study addresses this question by testing for the presence of earnings and employment spillovers of occupational licensing on a set of counterfactual occupations. The lack of clear or systematic definitions of "counterfactual occupations" has been a key shortcoming in the literature. I address this by defining these as occupations that use similar skills, which I measure using data from the Occupational Information Network (O*NET) database. Spillovers may come through two competing mechanisms as well as sorting effects. First, licenses can have negative wage spillovers by raising costly barriers to enter one occupation and redirecting and increasing labor supply to unlicensed occupations. Alternatively, occupational licensing may increase monopsony power because licenses make outside options costlier to enter. In such a setting, employment in other occupations may fall rather than rising because firms with market power hire fewer workers and pay lower wages, (Ashenfelter et al., 2010), particularly in smaller labor markets with fewer outside options. Licensing may also lead to sorting because of heterogeneous adjustment costs or differential impacts of licensing regulations across demographic groups. This is the first study to test for the presence of such broad labor market externalities across occupations.

I test for spillovers in three steps. First, in order to define a set of counterfactual occupations, I group occupations together based on their skill content. I use data from the O*NET database and non-parametric clustering techniques to group together occupations into clusters that require similar levels of key skills and receive roughly similar wages. The skills upon which I base these clusters come from Acemoglu and Autor (2011) and represent combinations of non-routine, routine, manual, cognitive, and interpersonal skills, an approach also taken in Dodini et al. (2020). This approach addresses a key need in the literature.[4] This is the first study to use this novel, skill-based approach to study the effects of labor market regulations in the United States. This provides a roadmap for future work to expand the set of applications for data on occupational skills.

Second, using newly available data from the Current Population Survey, I use the share of individual workers that indicate they are required to have a license as a proxy for the regulatory environment in each state (Kleiner and Soltas, 2019). This approach overcomes a core measurement challenge in the literature. As the key treatment variable, I calculate the share of workers licensed within a state-skill cluster cell outside one's own occupation (which I call the "focal occupation") to measure licensure exposure. My empirical approach uses microdata from the American Community Survey in a state border match design to compare the earnings of workers in the same occupation in local labor markets on either side of a common state border where the workers differ only in the share of the skill cluster outside

[4]The application of this clustering approach to occupational skills evolved concurrently with Dodini et al. (2020). An alternative to this approach would be to use empirically observed job transitions to cluster occupations. However, job-to-job transitions are endogenously determined by the structure of the labor market, including licensing laws. Skill clusters, therefore, measure a set of counterfactual options independent of the structure of local labor markets.

their own occupation that is licensed based on the CPS individual licensing measures. I define the local labor market by ACS Public Use Microdata Areas (PUMAs). Because the licensing environment is defined at the state level, state-level licensing shares are assumed to be exogenous to other local labor market factors. My estimates are nearly identical when including fixed effects for local labor markets, which strengthens the case for this assumption. I then test for differences in the effects of exposure to licensure across different subgroups, particularly across gender, race/ethnicity, nativity, and labor market size. This is the first study to examine both the existence of spillovers as well as how these spillovers differ across demographic groups. Using my estimates, I calculate the counterfactual distribution of within-occupation earnings were licensing regulations eliminated.

Third, I estimate the effects of licensing exposure on employment and worker composition in each focal occupation. That is, for the same occupation on either side of a state border, does having more licensure in a skill cluster reduce or increase employment in the focal occupation? Do the focal occupations differ in the types of workers they employ? The direction of this employment effect informs the underlying mechanism behind earnings spillovers. A positive employment spillover on other occupations is consistent with a labor supply mechanism, while a negative employment spillover is consistent with a monopsony mechanism. My composition estimates shed light on the sorting effects of these regulations and would be predicted in both a labor supply and monopsony framework.

Consistent with the prior literature, I find an average earnings premium of approximately 8-10 percent in occupations required to have a license in their state relative to the same occupation in non-licensed local labor markets on the other side of a state border. On the other hand, I find that a 10 percentage point increase in the share of licensed workers in the same skill cluster outside a worker's own occupation is associated with earnings that are 1.5-2% *lower* for that worker. In other words, if every other occupation in one's skill cluster became fully licensed, earnings in one's own occupation would decline by approximately 15-20%. These negative effects are stronger for women, non-Hispanic black, and foreign-born Hispanic workers, which is consistent with these demographic groups being less able to absorb the costs associated with licensure or differential effects of the regulations themselves. Because these groups are in the lower portion of the income distribution, these effects imply that licensing and regulation externalities contribute to local income inequality. I present graphical evidence of this effect by showing the counterfactual distribution of within-occupation earnings if licensing requirements did not exist in my sample. This counterfactual exercise suggests that eliminating occupational licensing would reduce earnings inequality within occupations by 2-4% across various measures such as the 90/10 and 10/50 percentile earnings ratios, while the overall Gini coefficient within occupations would fall by as much as 7%.

I find no evidence of a direct labor supply increase to the focal occupation. I find a statistically significant decline in the absolute number of workers in the focal occupation as a result of licensing in other occupations. The negative employment effects are strongest in smaller labor markets, which aligns with the recent monopsony literature (Rinz, 2018; Dodini et al., 2020). I also find that as a cluster outside the focal occupation becomes more licensed, the share of workers in the focal occupation who are women or have a Master's degree or PhD falls. In addition, the share of workers in the focal occupation that are Hispanic or foreign-born rises by over 8 percentage points as the cluster becomes fully licensed.

A placebo exercise in which I randomly assign occupations to clusters and recompute my estimates shows that unobserved factors correlated with earnings, employment, and the general local propensity to license occupations do not explain the relationships I observe. Licensing exposure in placebo clusters is uncorrelated with earnings, occupation composition, and employment. My findings are also robust to the inclusion of local labor market (PUMA) fixed effects. This specification limits identifying variation to only areas that share a border with multiple states. Unobserved differences in local labor markets correlated with licensing rules are, therefore, not driving my results. My findings also are robust to different choices about the optimal number of clusters and the sequential elimination of individual clusters from the analysis. I also perform the same analysis using simple cross-state variation similar to Kleiner and Soltas (2019) with data from the 2015–2018 CPS Outgoing Rotation Group and find similar results.[5] The pattern of results are also notably similar using a different measure of licensing intensity pulled from the text of licensing laws themselves (Redbird, 2016).

This paper contributes to the growing empirical literature on the effects of labor market regulations on workers. In addition to the growing field of research on occupational licensing, recent studies have examined the effects of enforcing non-compete agreements and have found that enforcement of these agreements reduces worker wages (Starr, 2019; Starr et al., 2021; Lipsitz and Starr, 2022; Balasubramanian et al., 2020), including possible negative effects on those unconstrained by these agreements (Starr et al., 2019). The main mechanism through which these negative effects take place is through a decrease in the number of outside options available to a particular worker, an increase in search and switching costs, a decline in worker mobility, and an increase in firm monopsony power.

Particular to the topic of occupational licensing, recent studies suggest there are sizable wage premiums associated with occupational licensing on the order of 10–30% (Kleiner and Krueger, 2013; Gittleman et al., 2018; Kleiner and Vorotnikov, 2017; Kleiner and Soltas, 2019; Thornton and Timmons, 2013). Reassuringly for my empirical approach, synthetic control and other panel estimates of the effects of occupational licensing are similar to the cross-sectional estimates found in other studies (Pizzola and Tabarrok, 2017; Thornton and Timmons, 2013).

The main mechanism through which these wage effects in the prior literature appear is through reductions in labor supply to licensed occupations of approximately 20% (Blair and Chung, 2019; Kleiner and Soltas, 2019), with some exceptions in occupations like nursing (DePasquale and Stange, 2016), coupled with licensed workers working more hours on the

[5] The main log wage regression coefficients are in Appendix Figure A17 and closely follow my main results for weekly earnings.

intensive margin (Bailey and Belfield, 2018; Kleiner and Soltas, 2019) and increases in prices in the product market (Adams III et al., 2002; Wing and Marier, 2014). In addition, the composition of workers shifts with licensing, with more women and black workers entering licensed occupations (Bailey and Belfield, 2018; Redbird, 2017), possibly to take advantage of the signal value of a license (Blair and Chung, 2018). Work on migration, which is pertinent to overall labor supply choices, suggests that licenses decrease interstate migration by as much as 36% (Johnson and Kleiner, 2017). Finally, and importantly, occupational licensing reduces labor market fluidity as measured by job changes and can explain nearly 8% of the total change in occupational mobility over the last twenty years (Kleiner and Xu, 2020).

On the topic of spillovers, a few important papers find notable effects of licensing requirements on occupations that perform substitutable functions. Licensing and credentialing requirements for physical therapists, namely those which govern direct access to patients, have negative effects on the wages of occupational therapists because many services are substitutable between the two (Cai and Kleiner, 2016). When nurse practitioners, who act as a substitute for physicians in many medical services, are given broader scope for their practice, physicians' wages fall, while nurse practitioners' wages rise (Kleiner et al., 2016).[6] In the paper most related to my analysis, Kleiner and Park (2010) examine the effects of broadening the scope of practice for dental hygienists on the earnings and employment of both hygienists and dentists. They find that as regulations that allow hygienists to be self-employed are implemented, wages for hygienists rise by 10 percent, and employment among hygienists increases, while earnings and employment for dentists both fall. The authors contextualize this result in a monopsony model in which tighter scope of practice regulations grant monopsony power to dentists, who tend to own their own practices and often house the services of hygienists.

This paper contributes to our understanding of the operation of regulated labor markets by identifying the broad effects of occupation-specific regulations on other occupations. In particular, this paper is the first to demonstrate that strict entry regulation comes at a broad cost: lower labor market earnings and employment for those in occupations that use similar skills. This study is also the first to show that these wage externalities are not the result of a pure labor supply shift but that occupational entry restrictions increase labor market rigidity and thereby exacerbate firm labor market power. My analysis also sheds light onto who bears the largest costs of these occupational regulations and shows that the costs disproportionately load on workers already more likely to be lower in the income distribution, resulting in an increase in earnings inequality. This analysis deepens our understanding of the trade-offs between the consumer protection benefits of entry regulations and the dispersed costs of licensure as they are imposed upon workers in general, most of whom play no part in the legislative negotiations that ultimately determine the scope of these regulations.

[6] Dillender et al. (2022) similarly find that earnings and lagged job postings both increased for nurse practitioners when their legal scope of practice expands.

2 Theoretical Frameworks for Spillovers

A host of papers present models of a competitive labor market in which barriers to entry into specific occupations will result in fewer workers entering the occupation (Kleiner, 2000; Kleiner and Soltas, 2019; Blair and Chung, 2019). But one piece missing from the current literature is the set of choices made by those who exit or who are prevented from entering the occupation due to higher entry costs and the spillover effects of those choices on the structure of the labor market.

Consider the simple graphical frameworks in Figure 1 depicting possible responses to licensing restrictions in an unlicensed occupation closely related to a licensed occupation. In Panel A, which represents a labor supply spillover in an otherwise competitive market, workers prevented from entering the licensed occupation due to entry costs enter this similar occupation at higher rates. This shifts out the labor supply curve S to S', resulting in higher labor supply at L' and lower wages at W'. The result is a combination of lower wages and higher employment. The size of the labor supply shift into this occupation depends on how closely the occupations are related in their skill dimensions, the ease of moving across occupations, and how prohibitive the licensing restrictions are for each prospective entrant.[7]

Those facing differential changes in barriers with a new licensing requirement or who are categorically ineligible to work in a licensed occupation will be more strongly affected in their occupation choices and therefore be the likely movers into unlicensed occupations. This might include women, who bear larger shares of home production responsibilities making occupational transitions more costly, foreign-born Hispanic workers most affected by citizenship, residency, or language requirements, or black workers, who are more likely than other racial groups to have a past experience with incarceration or experience labor market discrimination—statistical or "taste-based." This implies a composition shift among occupations.

As a brief example, consider the rising licensing requirements to being a physical therapist (PT) or occupational therapist (OT) cited in Cai and Kleiner (2016). Prior to the licensure of occupational therapy, some prospective entrants to PT might be deterred from PT and instead enter OT. As OT becomes more licensed, other prospective entrants may then be deterred from entering either occupation and instead enter something like athletic training, which requires a bachelor's degree in states where it is licensed, but in some states entirely lacks a governing body (Vargo et al., 2020). Even in the presence of a strong underlying skill endowment relevant to PT and OT, a larger share of workers enter the remaining, less-regulated occupation. This framework predicts higher employment and lower wages in athletic training.

In comparison to the competitive model, consider a model in which occupational licensing exacerbates monopsony power in the labor market. Such a model is discussed in Kleiner and Park (2010) in the context of dentists and dental hygienists in a single product market for

[7] In Appendix C, I discuss a model of skill transferability in a competitive labor market and how these parameters influence occupational choices when a licensing regulation is introduce.

dental services, but the monopsony context is worth exploring further. In Panel B, a person considering changing occupations into the licensed occupation but is deterred by the entry costs has fewer effective outside options. An entire branch of possible firms hiring in the licensed occupation becomes infeasible to such workers. This decreases the elasticity of labor supply to the firm, tilting the labor supply curve from S to S'. A monopsonistic firm then employs workers at wage W^M while limiting employment to L'. The result is a combination of lower employment and lower wages. In the prior example, raising licensing requirements in PT and OT may make entry from athletic training infeasible. A monopsonistic firm that employs athletic trainers may recognize this friction, hiring fewer new trainers and paying athletic trainers a lower wage because the threat of leaving the firm is less credible.

A monopsony search model can shed light onto this dynamic. Black (1995) proposes a search model in which the presence of "prejudiced" firms that refuse to hire black workers may lead to higher search costs for black workers as their choices of "unprejudiced" firms are rarer, which lowers their reservation wages and therefore increases monopsony power of the "unprejudiced" firms over black workers. I adapt this model to my setting wherein a worker may search for a firm match both within and across occupations. An occupational licensing requirement raised in multiple outside occupations acts as an increase in the number of "prejudiced" firms that refuse to hire an unlicensed worker in a particular occupation because they legally cannot hire them.

Following Black (1995), suppose there is a θ share of firms who, due to their product markets, will hire licensed workers with skills in cluster S, and (1-θ) share who will hire unlicensed workers in cluster S. Those with a license, l, and those without, n, face wage offers from "unprejudiced" firms, u, of ω_u^l and ω_u^n, while only licensed workers receive wage offers from "prejudiced" firms at ω_p^l. Parameter α is the utility value of job satisfaction in a firm-occupation match with a probability density function $f(\alpha)$. A worker searching for a job accepts a wage offer when $\alpha \geq u_r^l - \omega_j^l$, where $j = u, p$ and u_r is reservation utility. Given κ costs of the next search, a worker with a license in an occupation searches until the point she is indifferent, or when marginal search costs are equal to the marginal expected benefit of the next search:

$$\kappa = \theta \int_{\alpha_p^l}^{\infty} (\omega_p^l + \alpha - u_r^l) f(\alpha) d\alpha + (1-\theta) \int_{\alpha_u^l}^{\infty} (\omega_u^l + \alpha - u_r^l) f(\alpha) d\alpha \tag{1}$$

An increase in wages paid in firms and occupations in either the licensed or unlicensed sector raises the reservation wage of a licensed worker. A rise in the share of firms that only hire licensed workers, which may occur with new licensing legislation, ambiguously changes licensed worker welfare depending on the change in wages between licensed and unlicensed occupations and firms.

For a worker without a license, the search will continue until:

$$\frac{\kappa}{(1-\theta)} = \int_{\alpha_u^n}^{\infty} (\omega_u^n + \alpha - u_r^n) f(\alpha) d\alpha \tag{2}$$

An increase in the share of firms only hiring licensed workers in the skill cluster strictly increases the search cost and therefore lowers the reservation wage of an unlicensed worker in the cluster. Because firms recognize this, they offer unlicensed workers lower wages, and any measured elasticity of labor supply to the firm with respect to offered wages becomes more inelastic.[8]

From the product market perspective, as the cost of entry into competing product markets rises with licensing costs, product market power may increase. A simple example is the supply of massage therapists. Restricting the supply of independent operators reduces product market competition in addition to labor market competition. Recent research on the relationship between product market power and labor market concentration suggests the two are positively correlated (Marinescu et al., 2019; Qiu and Sojourner, 2019; Lipsius, 2018).

In the same framework, a worker that is part of a historically discriminated minority in the workforce (e.g. black workers, women) may find their outside options even more limited by occupational licensing. However, their individual returns to entering the licensed sector then rise relative to the alternative, and they may take advantage of the signaling value of a license (Blair and Chung, 2018). In this case, the wage premium for obtaining a license will be higher for those in these demographic groups relative to others in the group, while the wage spillover penalty will be larger in the unlicensed sector for these groups.

Many licenses contain requirements that may differentially increase θ depending on group characteristics. Requirements against any past felony conviction may differentially affect some black workers, while licenses whose exams are purely in English may negatively affect non-English speaking immigrants (half of which are Spanish speakers (Rumbaut and Massey, 2013)), and citizenship or residency requirements may disproportionately affect foreign-born workers. In that case, the spillover effect is expected to be larger.

This framework predicts that as licensing increases within a cluster, equilibrium employment in the remaining occupations will also fall as monopsonistic firms hire fewer workers. In addition, these negative wage effects will be larger in smaller labor markets due to fewer baseline search options. Labor market concentration and monopsony power have been shown to be higher in smaller labor markets where outside options are numerically limited by market size (Rinz, 2018; Dodini et al., 2020). The prediction of composition changes is the same as in a competitive model.

To summarize, the direction of any earnings and employment effects of occupational li-

[8] One might ask how important occupational licensing would be in comparison to other costs of switching occupations in a monopsony framework. According to Cortes and Gallipoli (2018), only about 15% of total occupation switching costs is attributable to task-specific adjustment costs, so given general skill cluster matching, these skill-based adjustment costs are likely to be small. Licensing, however, imposes large time costs that may outpace task-specific costs.

censing regulations can inform us about the underlying mechanism. The key difference in the competitive context in relation to the monopsony context is the direction of employment changes: increases in employment in unlicensed occupations are suggestive of labor supply shifts in a competitive model and employment declines are suggestive of a monopsony effect.

3 Data

To empirically test for spillover effects of occupational licensing, I bring together three main data sources: the 2015–2018 Current Population Survey (CPS) for state-specific licensing requirements for individual occupations; the Occupational Information Network (O*NET) dataset for details on the skill requirements of occupations; and microdata samples from the American Community Survey (ACS) from 2014–2017 for data on individual earnings, occupations, demographics, and sub-state geographic identifiers.

3.1 Current Population Survey

One major challenge to estimating the effects of occupational licensing is a lack of clear data on licensing requirements at the national or state level. Redbird (2017) painstakingly organized a list of licensing requirements back to the 1970s in order to measure the effects of licensing on wages. However, mapping the text of licensing laws onto occupational definitions as they are surveyed and coded by statistical agencies creates an important measurement problem. Many licenses cover only a small subset of workers in what would be considered a larger occupation category. For example, in Alabama, "anesthesiologist assistant" is a licensed occupation, whereas next door in Mississippi, it is not. Even at the level of 6-digit Standard Occupational Classification (SOC) code, "anesthesiologist assistant" is grouped together under the "physician assistant" code with other occupations such as "family practice physician assistant." "Physician assistant" itself is also separately licensed in both Mississippi and Alabama as a different occupation involving different responsibilities (Vargo et al., 2020).

This tension between statistical occupation categories and legal definitions is not rare, and, in fact, becomes more complex as the number of occupations increases. It is unclear how to reconcile these statistical challenges with direct measures of licensing laws without leading to significant measurement error in the treatment variable, which could lead to considerable attenuation bias—a bias exacerbated by the fixed effects models used in this literature.

In 2015, the CPS began asking individual workers questions regarding licensing and certification. I consider a worker licensed if the worker in the survey indicates 1) that they have an active professional certification or state or industry license; and 2) that any of those certifications were issued by a federal, state, or local government. This classification yields estimates of national licensing shares of approximately 22 percent, consistent with other surveys (Blair and Chung, 2019) as well as other papers using the same measure (Kleiner and Soltas, 2019; Cunningham, 2019).

Using CPS data from 2015–2018, I construct two key measures for my analysis as proxies for the policy environment within each state. First, following Kleiner and Soltas (2019), as a measure of policies affecting a single occupation, I calculate the state-occupation cell share of workers that are licensed. This abstracts away from individual determinants of receiving a license, which may be endogenous. This exercise also allows me to incorporate differences in sub-occupational licensing status into broader occupational categories in the CPS. Returning to the anesthesiologist assistant example, given that the "physician assistant" occupation in the CPS would include "physician assistant" and "anesthesiologist assistant," and "family practice physician assistant," if these sub-categories are differently licensed across states, my aggregated measure will capture this variation across states within a single occupation code.[9]

Second, using individual licensing status, for every occupation, I calculate the share of workers in the same skill cluster *outside* the excluded occupation (the focal occupation) that is licensed. This measure characterizes "exposure" to licensing from other similarly skilled occupations. Every state-occupation cell experiences a different measure of licensing exposure within its own cluster across states. This is the key treatment variable for my analysis. Notably, the approach using individual license shares as a proxy for the regulatory environment is validated in Kleiner and Soltas (2019) and is highly correlated with well-known licensing laws from other sources.[10]

3.2 American Community Survey

To construct my border match sample, I use data from the American Community Survey with geographic identifiers for Public Use Microdata Areas (Steven et al., 2019) on near each state border. Appendix Figure A1 shows maps of my border PUMAs in four Census Divisions. PUMAs map within states and across counties, are intentionally coincident with Metropolitan Statistical Areas in densely populated areas, and each contains at least 100,000 people. I categorize workers into 2010 Census occupation codes to match the licensing shares in the CPS. The dataset also contains data on sex, race/ethnicity, nativity, and the size of the working-age population (18–64) in the PUMA, which serves as my measure of labor market size.

One limitation of the ACS generally is how it measures determinants of hourly wages: earnings and hours. Baum-Snow and Neal (2009) explain the ways in which part-time workers systematically under-report hours in the survey, leading to implausibly large estimates of their

[9] To give an example of the measurement challenge, using OES employment weights and the statutes in the Northwestern Licensing Database (Redbird, 2016) to calculate the share of a state-occupation cell licensed, I compare the NLD to the CPS data. The correlation in licensing shares is 0.6. 61% of workers in the CPS who say they are required to have a license for their occupation would not be required to have a license under a binary (50% cutoff) licensing rule in the NLD. 48% of workers licensed under the NLD according to their occupation do not report needing a license in the CPS. I have replicated my baseline cross-sectional analysis using the list of regulations in the Northwestern Licensing Database (Redbird, 2016) as a measure of licensing intensity. The result is a set of estimates in a similar direction to my preferred estimates, though both are attenuated toward zero, particularly in measuring an occupation's own wage premium. See Appendix Figure A18.

[10] Their Appendix E details the econometric strength of this measure, and they find that the effect of applying an empirical Bayes estimate of license shares is relatively small, particularly in state-occupation cells of sizes larger than 10. Because clusters are larger than occupations, finite-sample bias is less of a concern for these measures.

hourly wages. In order to avoid these measurement issues, I follow others in the literature by dropping those with allocated earnings and using log weekly earnings as the outcome variable rather than hourly wages (Busso et al., 2013).[11]

I limit my sample to those age 18–64 who are in the labor force and report positive weekly earnings. Following Gittleman et al. (2018) and Kleiner and Soltas (2019), I eliminate all "universally" licensed occupations like physicians, lawyers, and truck drivers from my list of focal occupations because the effects of licensure and spillovers may differ substantially from other occupations, though my results are robust to their inclusion.[12] As seen in Table 1, my border estimation sample contains 1.3 million individuals across the 48 contiguous US states and DC in 244 PUMAs, 110 border match pairs, and 410 Census-defined occupations. The border sample is similar to the overall ACS sample along most dimensions except in the share of the population that is Hispanic or Asian or Pacific Islander and the share that is foreign born. This may be primarily driven by the exclusion of parts of coastal California that have highly concentrated Asian and Hispanic populations as well as cities in central and southern Texas. There is also a small difference in the share with a Bachelor's degree. Importantly, these sample areas are very similar in terms of their licensed shares, both within the focal occupation, and within clusters.[13]

3.3 O*NET

The Occupational Information Network (O*NET) database is the result of a survey fielded by the US Department of Labor. Incumbent workers and occupation experts are surveyed about over 400 attributes of each occupation. These include abilities required to perform the job, the type of tasks performed, the skill level of the job. The survey also includes variables on knowledge, work style, interests, and work context variables.

Using the 2017 O*NET data, I classify the levels of six important latent skill areas as defined in Acemoglu and Autor (2011) for each occupation. Conceptually, these measures are used elsewhere in the literature to explain skill and work task polarization, but they are also useful in this context to classify occupations by overall skill type (Autor and Dorn, 2013; Autor, 2014). These are:

1. Non-routine cognitive/analytical
2. Non-routine cognitive/interpersonal
3. Routine cognitive
4. Routine manual
5. Non-routine manual/physical

[11] While some of this earnings effect may be influenced by the intensive margin effect in which licensed workers work more hours than unlicensed workers, this equilibrium effect is important if spillovers also reduce the hours of unlicensed workers.

[12] The inclusion of universally licensed occupations only makes the estimates less precise.

[13] There is a similar difference in the border design in Blair and Chung (2019); this design, while internally consistent, may have limited external validity. However, my analysis using the full CPS sample (Appendix Figure A17) suggests the treatment effects are similar.

6. Non-routine interpersonal adaptability

The components in the O*NET questionnaire used to define these skills are listed in Table 2. These skills capture important characteristics about each occupation that go beyond educational requirements alone, but characterize the abilities, either acquired or endowed, that are essential for someone to perform in that occupation. Someone working in an occupation that requires routine, manual work is unlikely to easily transition to a job requiring intense non-routine cognitive skills. The imposition of a license to perform a job heavy in routine, manual work may influence the labor market for workers whose jobs heavily rely on the same underlying skill.

The O*NET data are collected according to SOC code definitions. Following (Acemoglu and Autor, 2011), I use Occupation Employment Statistics (OES) national figures to create a weighted average of these O*NET skill characteristics at the 2010 Census occupation level to match the occupation categories in the CPS. The final figure is a national employment-weighted average skill content for each Census occupation code across these six skill measures. In addition to these skill measures, I also calculate the median log wage for the national distribution of wages in each occupation from the CPS as an additional clustering criterion.[14]

4 Empirical Approach

4.1 Occupation Clustering

To classify occupations into similar groups based on their skill content and therefore define a set of counterfactual occupations, I use a hierarchical agglomerative clustering technique (HAC) (Sokal and Michener, 1958) because of its non-parametric properties and intuitive interpretation. This approach begins with all occupations in their own cluster then merges the closest occupations together based on the remaining "distance" between occupations and places them in the same cluster. As the allowed distance between cluster members increases, fewer clusters will form. Eventually, all occupations will be grouped in a single cluster. This non-parametric procedure forms a dendrogram (or tree) of these various cluster merges. The researcher using the approach has the option of choosing "cut" points to trim the tree at a set number of clusters or a maximum distance between cluster members. It flexibly does not require an occupation to be a member of a larger cluster and has the advantage of being able to handle varying densities across clusters, which is a noticeable feature of the O*NET skills data.[15]

[14] Including median wages helps to minimize the possibility of matching occupations with vastly different labor market outcomes. For example, though a professional athlete and a freight laborer may use similar physical and cognitive skills, the returns to these may differ dramatically. Appendix B provides justification for using these six skill measures as inputs into the clustering algorithm rather than an alternative principal-component measure of skills.

[15] For example, there are hundreds of occupations in the O*NET data which separately define the functions of workers who operate specific machinery in production or construction. The specificity of these occupational definitions without much difference in the skills necessary to operate these machines makes clusters that include these occupations very dense.

Figure 2 presents a toy example of HAC. The left pane represents data points along two dimensions, and the right pane represents the dendrogram of the hierarchy. First, groups 5 and 6 merge to form the purple cluster. Next, this purple cluster merges with group 4 to form the blue cluster. Next, groups 1 and 2 merge to form the yellow cluster. Then group 0 merges with the yellow cluster to form the red cluster. Finally, group 3 is merged with the blue cluster to form a green cluster. Along the progression of these merges, the analyst may choose either a maximum distance between cluster members (the y-axis measure of distance between points when they are first connected by a horizontal bar) or by selecting a set number of clusters (the number of vertical lines intersecting with a horizontal line at some distance cut point). Depending on the technique chosen to validate a number of clusters as "optimal" or the institutional details known to the researcher, there could be anywhere from 2 to 6 clusters in this example.

With this technique in mind, I pursue the following steps: first, I calculate the correlative distance between each occupation across these six occupational skill characteristics as well as the national median log wage for each occupation. This distance is simply one minus the Pearson correlation coefficient between occupations on all seven measures. The advantage of this measure is that it is not sensitive to the scales of the inputs as a Euclidean or other distance measure would be. The result is a single matrix with range [0,2] for every occupation-occupation dyad. Second, with this matrix of dissimilarity, I use the HAC algorithm to group together occupations based on their distances step by step and form a dendrogram of the relationships. Third, I calculate a data-driven "optimal" number of clusters and select the corresponding cut point. I use the subsequent cluster definitions in my models.

There are three main researcher choices that must be made when performing any HAC exercise. The first choice relates to which input characteristics to use. The literature on skills and trends in wages has focused much attention on the six skills I use in my clustering analysis (Acemoglu and Autor, 2011). These skills prove useful not only in examining wage trends, but also in classifying the skills used across occupations. I provide detailed justification—including empirical tests—for using these particular skills for clustering rather than other aspects of an occupation available in the O*NET data (such as its principal components) in Appendix B. Put briefly, the computer science literature states that in many cases, the principal components of the data, while capturing the greatest variation across the attributes, do not capture the *cluster* structure of the data as well as using a subset of the variables (Yeung and Ruzzo, 2001).

The second choice is what parameter of distance to choose when merging two clusters that have already formed. I use what is called "average linkage distance," which uses the mean data value of all points in formed clusters when determining the distance between clusters, i.e. from cluster mean to cluster mean. Unlike measures such as "single" or "complete" linkages, which, respectively, use the nearest or the furthest unit of the cluster to calculate distances between clusters, the average linkage approach is more robust to outliers within clusters.[16]

[16]Depending on the structure of the data, this choice may be consequential, but in the context of skills in

The third choice is how many clusters to use in the final analysis. To support the choice of twenty clusters for my main analysis, I present the results of my validation exercises here. I use four validation measures common to clustering applications: Silhouette (Rousseeuw, 1987); Dunn's index (Dunn, 1974); SD index (Halkidi et al., 2000); and the C index (Hubert and Levin, 1976), though there are dozens from which to select. The first two measures are based on maximizing their index values, while the latter two are based on minimizing their values. It is also useful to look for structural breaks in the index values. Figure 3 shows the results using these four measures. Panel A suggests that the optimal number of clusters is likely below 18, as the index bottoms out above this number, but is markedly higher at lower numbers of clusters and for clusters above 23. Panel B strongly suggests the optimal number of clusters is somewhere between 14 and 20. Panel C suggests the optimum ought to be below 13 or perhaps 19-22. Lastly, Panel D suggests the optimum is either 12–13 or 23–30, although the index values for 14–23 are stable and relatively low. Based on the totality of these tests, there is considerable overlap in the optimal number from the mid-teens to twenty. For transparency, I calculate and plot a range of estimates across the number of clusters from 4 to 20 to report the coefficients of interest under larger, less compact clusters (4) relative to smaller, more compact clusters (20) in the appendix. As the number of clusters gets larger, cluster size falls, making the occupations more narrowly related along skill dimensions, but identifying variation within the cluster will also fall. In my estimates, treatment effects above approximately ten clusters are robust to increasing the number of clusters and consistent across my outcomes of interest. In my main estimates, I present the results at twenty clusters.

As a test of the sensibility of the cluster assignments, I present the five most frequent occupations in each cluster at their most compact (20 clusters) in Appendix Table B1. The definitions appear sensible, and many occupations, though a part of separate industries or Census occupation groups, make logical companions to each other. For example, personal care aides may use similar interpersonal, management, cognitive, and physical skills as waiters, though they are separated by industry definitions. Police detectives and private investigators use similar investigative, cognitive, and management skills as construction and building inspectors despite being in very different industries. A child care worker can personally attest to taking on multiple roles as a fitness/recreation worker, coach, and umpire—often simultaneously.

4.2 Border Match Design

In the experimental ideal, a researcher choosing to study the effects of occupational regulations like licensing on the labor market would randomly assign some occupations in some jurisdictions and clusters to impose a licensing requirement and then observe market equilibrium outcomes in the treatment group in comparison to a status quo control. To approximate this experimental ideal, I construct a matched border sample of Public Use Microdata Areas

the O*NET data, the distinction is not meaningful for my results.

(PUMAs) from the American Community Survey with contact with a common state border. My estimating equation then includes state, occupation, and border fixed effects:

$$y_{iocms} = \beta_0 + \beta_1 LicensedShare_{os} + \beta_2 LicensedShare_{cs}^{-o} + X'\beta_3 + \delta_o + \gamma_s + \tau_m + \varepsilon_{iocms} \quad (3)$$

This equation characterizes outcome y for individual i in occupation o in cluster c in state s on the state-state border m.[17] Coefficient β_1 captures the earnings effect of licensing individual i's entire *own* occupation category on the earnings of individuals in occupation o in state s, whereas β_2 captures the effect of fully licensing all other workers in cluster c *outside* of occupation o (the focal occupation) in state s. Outcome y is log weekly earnings for my main specification. To measure composition effects, I also estimate linear probability models on race/ethnicity categories and broad education categories as well as a binary indicator for being age 18-25. X is a set of individual controls for sex, race/ethnicity, age, and age squared. I omit other controls which may be directly affected by licensing such as education to avoid collider bias. For the composition regressions, I omit other individual controls.

Rather than relying purely on the assumption of state-wide similarity in labor markets across licensing status, the border match design compares workers in the same occupation on two sides of a state border where the state line creates differences in their occupational licensing status and the status of other occupations in their skill cluster. The border fixed effect holds constant the shared features of the local labor market, and the state fixed effects hold constant other attributes of their state as well as the regulatory conditions that affect the distribution of earnings and employment in the state (e.g. minimum wage laws, education regulations, overall state propensity to license, etc). Due to the simplicity of the assumptions, many studies use this approach, including in the occupational licensing literature (Blair and Chung, 2019; Black, 1999).

As an example, consider the region around Washington, DC. While the three jurisdictions (Virginia, DC, and Maryland) have different regulations across various occupations, the labor markets are extremely similar along other dimensions such as local labor demand and the overall supply of workers. All pairwise combinations of these borders—VA-DC, MD-DC, VA-MD —contribute to identification of the effects of licensure for each occupation. In this design, unobserved characteristics of local labor markets that may affect employment and earnings are absorbed in the border fixed effect, and, conditional on this fixed effect, licensing shares are arguably exogenous. To ensure that other broad characteristics of the local labor market in the PUMA are not driving these results, I estimate my border match sample including PUMA fixed effects in Section 5.5. In this specification, identification comes purely from PUMAs that share borders with multiple states. Results from this exercise show that my border design is

[17] For example, the California-Oregon border would have its own identifier, while the California-Nevada border would have another. For PUMAs that share borders with multiple states, I stack the sample and divide the sample weights by the number of borders.

robust to unobserved characteristics of the local labor market.

One concern about a border match design of this nature is the possibility of spatial spillovers and cross-state commuting. If individuals move across the state border to avoid occupational regulations or if workers in one jurisdiction commute to and work in another jurisdiction, this should bias my estimates of the labor market effects of licensure towards zero, meaning my estimates would be a lower bound. This is because licensed workers may live in one jurisdiction and contribute to the licensing rate in that state while actually working with their license in another. However, because licensing rates are calculated at the state level and not PUMA level, this measurement error is likely to be small. That my results are almost identical with PUMA fixed effects strengthens the argument. Similarly, workers less exposed to licensure in their own state may nevertheless experience effects from licensing in the bordering state. With the inclusion of PUMA fixed effects, identifying variation comes from a smaller set of local labor markets, but the results are similar. I also estimate a simple model that examines differences across states rather than across shared state borders and find similar results (see Appendix Figure A17), meaning that cross-border spillovers may be relatively small. Finally, cross-state migration is, by itself, affected by licensing, meaning that my border design will capture some of these equilibrium effects of either reduced interstate mobility or avoidance behavior (Johnson and Kleiner, 2017).

To examine heterogeneous treatment effects, I interact my measures of own-occupation licensure and cluster licensure outside the focal occupation with demographic indicators for sex, race/ethnicity groups, nativity (native- vs foreign-born), and quartile of labor market size (the population of working adults with positive earnings in the PUMA) in separate models. Labor market size is a particularly important measure, as theory and empirical evidence both suggest that smaller labor markets experience greater labor market concentration and therefore monopsony power (Rinz, 2018; Dodini et al., 2020).

To examine the overall employment effects of licenses and license spillovers, I collapse the data and estimate employment in the occupation-PUMA cell as an outcome variable and run the same specification excluding individual characteristics. The own-occupation effect (β_1) measures the effects of licensure on employment in that occupation itself, while β_2 captures the employment spillovers. A pure labor supply explanation predicts a positive β_2 coefficient as licensing pushes workers into other occupations. A negative β_2 spillover coefficient on employment in the focal occupation is suggestive of monopsony power if earnings effects are also negative in my individual models.

5 Results

5.1 Earnings Premium and Spillovers

I first present the results for the overall earnings effects of widespread occupational licensure. Figure 4 plots the coefficients and confidence intervals for occupation spillovers for 4 to 20 clusters and indicates that having a license for one's own occupation leads to an earnings premium of approximately 8%, a finding consistent with the findings in the prior literature. On the other hand, increasing licensing rates in all other occupations in one's own skill cluster by ten percentage points reduces weekly earnings in the focal occupation by 1.5–2.5% on average. The confidence intervals rule out average effects as small as -0.5–1% and effects larger than -3%. Given that the validated optimum number of clusters is somewhere in the 13–20 range, the effects are concentrated around 1.5-2%.[18] To ease interpretation, I present the rest of my estimates using 20 skill clusters, the most conservative set of estimates. The results from varying the number of clusters are in Appendix A, and each follows a similar pattern to the overall estimates.

I find substantial heterogeneity in this effect across gender as well as race/ethnicity and nativity as detailed in Figure 5. Panel A shows the effects of licensure in one's own occupation, while Panel B shows the spillover effects of cluster licensure. While women in licensed occupations receive a larger earnings premium than men, they also experience a larger earnings spillover penalty. Women receive an earnings premium of 17-18% in licensed occupations relative to other women in the same occupation that are not licensed, while increasing skill cluster licensing requirements by 10 percentage points leads to a reduction in their earnings of approximately 3%. The same coefficient is less than 1% for men. Non-Hispanic black workers and Hispanic workers experience larger earnings spillovers than their Non-Hispanic white counterparts. The point estimate for Hispanic workers is around -2% for a ten percentage point increase in cluster licensure compared to -1.5% for Non-Hispanic white workers, though the estimates are less precise at 20 clusters. Non-Hispanic black workers experience the largest penalty, with a point estimate of approximately 2.8%. The large relative penalty for Non-Hispanic black workers may be due to licensing requirements that prohibit those who have been convicted of a felony from obtaining a license, an idea explored in Blair and Chung (2018; 2019). As licenses that exclude those who have been convicted of a crime increase, the set of occupations in which someone with a set of skills may work after conviction narrows. The returns to obtaining a license as an ability signal (or a signal of never having been convicted) may be higher in this case (Blair and Chung, 2018).

Most of the negative earnings spillover effect on Hispanic workers is be driven by foreign-born Hispanic workers. The estimates indicate that there is essentially no earnings premium for foreign-born Hispanic workers in licensed occupations, perhaps because a smaller share of Hispanic immigrants can obtain a license when compared to other immigrant groups, be it for education, language, or legal status reasons. Spillover effects for a ten percentage point increase in cluster licensure are nearly 3% compared to just over 1% for native-born Hispanic workers. Given the young age, relatively low educational attainment, and migrant status of foreign-born Hispanic workers, other outside options for foreign-born Hispanic workers may be lower than

[18]For ease of reading, I plot the point estimates of "own-occupation" effects without standard errors because these are not necessarily the estimates of interest, but are instructive for the validity of comparing my point estimates to other studies.

their native-born counterparts. In particular, citizenship or permanent residency requirements for many licenses may preclude many foreign-born Hispanic workers from entering a variety of occupations, which strongly limits their choice set. Both a direct labor supply effect into unlicensed occupation and a monopsony effect could explain this difference. In the monopsony case, the threat of leaving a firm to pursue another job or another occupation may be limited by concerns about legal work status.

Given the presence of possible statistical or taste-based discrimination against Non-Hispanic black workers as well as the additional imposition of citizenship or residency requirements for foreign-born workers, I expect spillover effects to be largest for foreign-born black workers. The estimates show that this is, indeed, the case. Native-born black workers experience spillovers of 2.5% with a ten percentage point increase in cluster licensure, while foreign-born black workers experience spillover effects of 4%.[19]

Finally, Figure 6 shows that there is a clear relationship between the intensity of the earnings effects of licensure and labor market size. The largest labor markets (Quartile 4) exhibit a smaller earnings premium in licensed occupations (4-5%) and no spillover effect. For the other three quartiles, this relationship intensifies as market size declines. In the bottom three quartiles, the own-occupation effect is consistent at approximately 10% for full licensure, while the spillover effect is as large as -3.2% in Quartile 1 compared to -1.2% in Quartile 3 for a 10 percentage point increase in licensure.[20]

These results suggest that there are substantial earnings spillovers of widespread occupational licensing within a worker's skill cluster and that the effects are highly concentrated among those that already are disproportionately lower-income and are less likely to be able to absorb the costs of licensing requirements. In addition, the spillovers are strongest in smaller labor markets that are likely to be less saturated with job openings and networks in which to search for a job.

5.2 Composition Effects

In addition to direct earnings effects, licensing spillovers may shift the distribution of workers within occupations in terms of educational attainment, sex, nativity, or race/ethnicity depending on differential ability to absorb the costs or returns to obtaining a license. To test this, I estimate linear probability models on binary indicators for sex, education categories, race/ethnicity groups, nativity, and an indicator for being age 18–25 using the same specification as my earnings model, except I exclude other individual controls. I again plot the coefficients and confidence intervals for within-cluster spillovers set at 20 clusters.

Figure 7 shows that as other occupations in the cluster become more licensed, the share of workers in the focal occupation who are women or who hold an advanced degree falls. Master's

[19]In contrast, due to the highly selective nature of immigration to the United States from European countries, there is no detectable earnings premium nor spillover effect for foreign-born, Non-Hispanic white workers. These results are available upon request.

[20]Estimates varying the number of clusters are in Appendix Figure A6.

degrees fall by 0.75 percentage points with a 10 percentage point increase in cluster-wide licensure outside the focal occupation. Relatedly, the share of workers in the focal occupation that is Hispanic or foreign-born increases significantly. Increasing cluster licensure by 10 percentage points leads to an increase in the share of workers in the focal occupation that is Hispanic or born outside the US by 0.8 and 1 percentage points respectively. These are the largest spillover effects I find across all outcomes.

These results indicate that as other occupations in the skill cluster become more licensed, there is not a large influx of those with lower levels of education (e.g. high school graduates without a college degree) shifting into the remaining unlicensed occupations, although the most advanced degrees do decline marginally. It does not appear that shifting human capital, per se, is responsible for the decline in earnings. Rather, there is a shift in the gender and race/ethnicity composition of the focal occupation, as well as a marginally significant increase in the share of young workers age 18–25. Widespread licensing appears to push some men (women) out of (into) licensed occupations and into (out of) the remaining unlicensed occupations in the skill cluster, as evidenced by the fact that the share of women in the focal occupations shifts downward. Hispanic workers and foreign-born workers filter out of licensed occupations in the skill cluster and into the remaining unlicensed occupations.

5.3 Employment

To understand the other mechanisms underlying the earnings effects I observe, I estimate a border match model of employment within each occupation-PUMA cell.

Figure 8 indicates that overall employment in each occupation falls by approximately 5 workers when the occupation is fully licensed. However, as licensure increases across the cluster, overall employment in the focal occupation *falls* by 20–30 workers when the rest of the cluster is licensed. Given that the ACS is a 1% sample, this implies overall negative labor supply effects of approximately 500-3000 workers in the typical occupation-PUMA cell. If occupational licensing increases labor market power, monopsonistic firms may employ workers at rates lower than they otherwise would in a competitive market, leading to effects consistent with the observed declines in employment I find.

Like the earnings effects discussed previously, the employment effects differ widely across labor market sizes. Figure 9 shows that the negative coefficients on employment in the focal occupation are particularly pronounced in smaller labor markets. The effect is approximately 45 fewer workers in the focal occupation in the smallest labor markets, compared to zero for the largest.[21]

Taken together, these results indicate that widespread licensing in a skill cluster lead to negative employment effects. This is particularly true in smaller labor markets. The strong negative employment and earnings effects of licensing spillovers appear suggestive of monopsony power, which I discuss in Section 6.

[21] Estimates varying the number of clusters are in Appendix Figure A7.

5.4 Distributional Effects

My main results suggest that occupational licensing regulations have negative earnings spillovers for workers that use similar skills and that these effects are concentrated among those already likely to be lower-income workers. To contextualize these effects in the distribution of incomes, I present graphical evidence of the counterfactual kernel density distribution within occupations of predicted weekly earnings in my sample if licensing were set to zero for all workers, both for their own occupation and others in their skill clusters, using Equation 3. The various fixed effects in this model remove variation over geographic space through the state border fixed effect, occupation through the occupation fixed effect, and states through the state fixed effect, so the distributions I measure are conditional or within-group distributions. This explains the relatively uneven densities I estimate, which appear bimodal in the upper half of the distribution and which we would not expect in an unconditional distribution. Notably, this counterfactual exercise does not capture the effects of changes to employment across occupations or moving some workers out of employment altogether but holds constant the occupational and spatial distribution of employment in my sample.

The results are in Figure 10. Panel A shows that after eliminating licensing in the sample, predicted weekly earnings shift rightward across most of the conditional distribution. Panel B shows the differences in the densities and suggests that there is a general shift for earnings below \$1,000 per week. More narrowly, there is a substantial change in the density moving earnings from approximately \$500 per week to approximately \$600 per week. There is also an increase from approximately \$1,000 per week to over \$1,100 per week and a decrease above \$1,400 per week, suggesting a compression effect in the distribution of predicted earnings.

Table 3 provides summary measures of inequality in the distribution of predicted weekly earnings in this counterfactual exercise. There are significant changes in within-group inequality as a result of eliminating occupational licensing in my sample. The ratio of the 90th to 10th percentile of weekly earnings would fall by nearly 4%, and the ratio 90th to 50th percentiles would fall by 2.5%. Much of the decline in the 90/10 ratio comes from increases in the 10/50 ratio, meaning that despite the median moving upward, the 10th percentile increases at a faster rate. Overall, the predicted Gini coefficient within the conditional distribution falls by nearly 7%.

Overall, this exercise implies that if a portion of existing licenses were eliminated, the distribution of earnings in the labor market would be significantly higher, with many of those gains accruing to workers below the median, resulting in a decline in earnings inequality. Because many workers in "universally" licensed professions earn particularly high incomes (e.g. physicians, attorneys, pilots), the results also imply that eliminating licenses for which there is not a national consensus for their usefulness (or where states differ in their licensing rules) would reduce earnings in the unconditional distribution of earnings as well by pulling up the bottom of the distribution. While I cannot measure general equilibrium changes in inequality coming through shifts in employment, the changes within occupations are substantial.

5.5 Robustness to Alternative Explanations

Given the lack of time-varying treatments in my empirical design, it is important to consider alternative explanations that may drive the relationships I have presented. In particular, many policies change across state borders, so there may be some unobserved policy difference that may differentially be correlated with employment/earnings and the general propensity to license occupations. If this is the case, the relationship between cluster licensure and earnings should hold regardless of the exact assignment of skill cluster because it is high *overall* licensure that matters, not cluster-specific licensure. To test this relationship, I perform a placebo exercise in which I randomly assign with equal probability each occupation to be a part of one of twenty clusters. I then use the CPS to calculate the licensed share of workers outside the focal occupation that are licensed within their placebo cluster. I then perform all of my main estimates using these shares with the same specification as Equation 3 in the ACS. If the licensing environment is correlated with state variables that are also correlated with the distribution of earnings, then the relationship between licensing exposure and earnings and employment should not significantly change.[22]

The results of this exercise are in Figures 11 and 12. Panel A of Figure 11 shows that licensing exposure within placebo clusters results in zero overall earnings spillovers. This relationship holds across all subgroups with the exception of native-born Hispanic workers. If anything, the general propensity to have high levels of licensure may be weakly *positively* correlated with earnings for racial/ethnic minorities (though not statistically significant) when considering placebo clusters, which runs counter to the large, negative effects noted in Figure 5. Similarly, Panel B shows that there is no relationship between occupational composition and licensing exposure in placebo clusters, indicating that the propensity to license does not reflect occupational composition difference across localities. With regards to employment, Figure 12 shows that there is no general relationship between overall employment in each occupation and licensing exposure in placebo clusters. When considering labor market size, there is a slightly positive relationship between employment and the tendency to license in the largest local labor markets, though the relationship is not large nor statistically significant for the other three quartiles.

The results of this exercise greatly strengthen the case for a causal interpretation of the spillover effects I have identified. By holding constant the other aspects of individual workers, occupations, state characteristics, and border pairs and showing that licensing exposure within placebo clusters does not result in significant estimates, I show that local differences in the propensity to license their occupations that may be correlated with unobserved determinants of employment and earnings are not a significant driver of my results.

As an additional test that unobserved characteristics of the local labor market (PUMA)

[22] Another indication that overall licensure is not a significant driver of my results arises from the fact that the spillover effects within clusters are small and not statistically significant below five clusters when clusters are large and there is only minimal differentiation between the clusters.

that may be correlated with licensure are not driving my results, I estimate my border sample with PUMA fixed effects and include "universally" licensed occupations. In this specification, identification comes from PUMAs that border multiple states. Appendix Figures A8, A9, and A10 show these results for the overall estimate, by sex, and by race/ethnicity, respectively. These estimates are nearly indistinguishable from my baseline estimates and indicate that unobserved determinants of wages in the local labor market are not biasing my baseline model.

To ensure that my results are not driven by any particular cluster definition, I re-estimate my earnings regressions at 20 clusters while sequentially eliminating a cluster at a time. This allows me to pinpoint if my results are driven by any particular cluster, large or small. Figure A11 indicates that the overall earnings estimates are not sensitive to any particular cluster. For two of the clusters, my estimates fall from -0.15 to -0.1, though the difference is not statistically significant. For these tests by gender and race/ethnicity, see Appendix Figures A12 and A13.

I also show the employment effects regressions in this same format in Figure A14. The effects on total employment, while visually sensitive to the exclusion of Cluster 1, are not statistically significantly different upon excluding it. There is still a sizable negative employment effect. I show a similar graph for my composition regressions as well in Appendix Figures A15 and A16.

To ensure that the population composition of my border sample is not driving my results, I use the Current Population Survey and simple cross-state variation in cluster licensure to estimate the same models but without the border pair fixed effects. The results in Appendix Figure A17 show a similar wage premium to Kleiner and Soltas (2019) and spillover estimates very similar to my border match design. It is, therefore, unlikely that sample selection in my border areas nor peculiarities in cross-border commuting and/or spatial spillovers are driving my results.

Finally, abstracting away from the measurement issues discussed in Section 3, I use the Northwestern Licensing Database (Redbird, 2016) to estimate the earnings spillover effects of licensure in my border match design and present those estimates in Appendix Figure A18. The result is an attenuated own-occupation earnings premium and a slightly smaller spillover effect compared to my base model. That the attenuation is more pronounced in the own-occupation effect is notable because individual occupations are smaller and more likely to be subject to measurement error than larger clusters that are aggregations of several occupations. However, the pattern of the results strongly supports the results of my preferred method with a very different data source.

6 Discussion

The pattern of lower earnings and lower employment in the focal occupation as a result of cluster-wide licensure is consistent with an increase in monopsony power in the local labor market.

Two key implications of monopsony theory are: 1) that even firms in what are ostensibly competitive labor markets can exhibit monopsony power if there are substantial costs to the worker for a job change; and 2) firms with monopsony power will employ fewer workers and pay lower wages than otherwise equivalent firms in competitive local labor markets (Ashenfelter et al., 2010).

I argue that monopsony power is not only a function of the costs of within-occupation switching across firms, but also of a worker's ability to leave the local labor market, switch occupations, or both. This view is supported by recent work that explores the use of more comprehensive definitions of a "local labor market" for workers in the measurement of the effects of labor market concentration and concludes that incorporating outside options is an important component (Schubert et al., 2019; Dodini et al., 2020). It is clear from the past literature that licensing increases labor market rigidity across occupations. Kleiner and Xu (2020) find that workers that are licensed are 24% less likely than unlicensed workers to have recently switched into their occupation. That transitions between occupations fall logically fits into a monopsony framework in which incumbent workers cannot credibly threaten to leave a low-paying firm. As licensing increases the cost of leaving a firm to pursue outside options within and across skill clusters as well as across state lines, the set of available options that are feasible for them to enter shrinks, which may exacerbate the low elasticity of labor supply to the firm in highly licensed areas as well as drive down employment in those areas as firms scale back new hiring.

There is also evidence from the monopsony literature that the elasticity of labor supply to the firm is lower for women than it is for men, implying greater monopsony power in the labor markets employing women (Ransom and Oaxaca, 2010; Ransom and Lambson, 2011; Barth and Dale-Olsen, 2009; Hirsch et al., 2010). This is consistent with my findings of far greater earnings spillover effects for women.[23]

The literature also suggests that immigrants supply labor to the firm much less elastically than their native-born counterparts, which Hirsch and Jahn (2015) predict leads to a predicted 7% wage penalty. Taste-based discrimination may be far more consequential for wages in monopsonistic labor markets, affecting historically discriminated groups such as African Americans (Berson, 2016; Webber, 2015; Black, 1995) or women (Fanfani, 2018). These two points together may partially explain why native-born and foreign-born Non-Hispanic black workers and women face the largest earnings penalty.

Finally, the case for a monopsony explanation is bolstered by the observation that both the negative labor supply spillovers and earnings penalties are stronger in smaller labor markets. The literature on labor market concentration suggests that smaller labor markets experience higher levels of concentration and also exhibit a stronger negative relationship between concentration and wages (Rinz, 2018; Dodini et al., 2020). Switching costs may be lower in large

[23]This also is related to the fact that women generally perform more non-routine, cognitive work than men on average, and these tasks as performed by those with more education are more exposed to monopsonistic behavior by firms (Bachmann et al., 2019; Dodini et al., 2020).

labor markets because of the physical proximity of available jobs and a wide set of available choices from which a worker may select. Relatedly, smaller labor markets may also imply a smaller product market for services performed by licensed workers. Limiting the entry of product market competitors in a smaller market leads to larger relative changes in product market power, which is positively correlated with labor market concentration (Marinescu et al., 2019; Lipsius, 2018; Qiu and Sojourner, 2019). For example, a massage therapist in a small town may be one of only a few producers of that service, whereas, in a larger labor market, that is unlikely to be the case. The imposition of costly licensing requirements leads to relatively larger market share changes in both the product and labor markets for that service in smaller areas. Taken together, a reduction in market power by employers would increase incomes across the distribution, but particularly for lower-income workers.

7 Conclusion

This analysis has presented the first evidence of substantial labor market spillovers from occupational licensing in the United States using a border match design. I find that occupations that use similar skills to licensed occupations experience a fall in weekly earnings of approximately 1.5% as a result of a 10 percentage point increase in licensure. I also find evidence of falling equilibrium employment and statistically significant increases in the share of workers that are women, foreign-born, and Hispanic as a result of licensure in other occupations. The earnings penalties are notably larger among women, foreign-born Hispanic workers, and Non-Hispanic black workers and are as large as 3.5-4% for a 10 percentage point increase in cluster licensure rates. That total employment in related occupations falls is consistent with a monopsony model in which licensure increases search and adjustment costs, reduces a worker's outside options, and reduces a monopsonistic firm's incentives to hire new workers. Eliminating or reducing the labor market frictions that come from licensing would increase earnings for many workers, particularly those at the bottom of the distribution, and significantly reduce pre-tax earnings inequality within occupational groups.

While the analysis presented here shows significantly lower employment as well as worker composition shifts as a result of licensing spillovers, I am limited in my ability to assess just how strongly these earnings penalties are correlated with markers of labor market power such as concentration. Future work in this area may attempt to test the effects of changes in occupational licensing statutes and labor market power in particular industries or occupations. In addition, though my cross-sectional estimates of the wage premium to licensure closely tracks dynamic and panel estimates in the literature (e.g. Pizzola and Tabarrok (2017)), I am limited by the available data to cross-sectionally identifying the effects of occupational licensing on other workers. Future work may explore dynamic changes to earnings and employment and possible monopsony power over time.

Occupational licenses are often justified by advocates as being in the best interest of consumer health and safety. One of the consequences of these regulations, intended or unintended, is a meaningfully large earnings premium for licensed workers.

At the same time, raising barriers to entry across more and more occupations may have unintended consequences for other workers. This analysis suggests that as strict labor market regulation grows, workers who might otherwise choose to work in an occupation *but for* the existence of the license are made worse off and that these effects are most keenly felt by workers already more likely to be financially disadvantaged. As a result, occupational licensing significantly increases predicted earnings inequality.

The employment and earnings effects of licensing and other labor market regulations, if broadened to include more occupations, may lead to labor market conditions consistent with more pronounced monopsonistic behavior by firms. In that case, while some workers may be better off individually once they get a license, the imperfections induced by strict entry regulations lead to other workers having fewer opportunities for advancement, making most unambiguously worse off due to the costs of the restrictions. These represent significant externalities. Policymakers should weigh the possible health and safety benefits of occupational licensing against the possible costs: the negative labor market effects of these regulations on workers that may not be party to the negotiations between the professional or political entities involved.

References

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

Adams III, A. Frank, John D. Jackson, and Robert B. Ekelund Jr.. 2002. "Occupational Licensing in a "Competitive" Labor Market: The Case of Cosmetology." *Journal of Labor Research*, 23(2): .

Ashenfelter, Orley C, Henry Farber, and Michael R Ransom. 2010. "Labor Market Monopsony." *Journal of Labor Economics*, 28(2): 203–210.

Autor, David. 2014. "Skills, Education, and the Rise of Earnings Inequality Among the "Other 99 Percent"." *Science*, 344(6186): .

Autor, David H., and David Dorn. 2013. "The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market." *American Economic Review*, 103(5): 1553–97.

Azar, José, Ioana Marinescu, and Marshall Steinbaum. 2020. "Labor Market Concentration." *Journal of Human Resources* 1218–9914R1.

Bachmann, Ronald, Gökay Demir, and Hanna Frings. 2019. "Labour Market Polarisation and Monopsonistic Competition."Technical report, Working Paper.

Bailey, Thomas, and Clive R Belfield. 2018. "The Impact of Occupational Licensing on Labor Market Outcomes of College-Educated Workers."

Balasubramanian, Natarajan, Jin Woo Chang, Mariko Sakakibara, Jagadeesh Sivadasan, and Evan Starr. 2020. "Locked In? The Enforceability of Covenants Not to Compete and the Careers of High-Tech Workers." *Journal of Human Resources* 1218–9931R1.

Barth, Erling, and Harald Dale-Olsen. 2009. "Monopsonistic Discrimination, Worker Turnover, and the Gender Wage Gap." *Labour Economics*, 16(5): 589–597.

Baum-Snow, Nathaniel, and Derek Neal. 2009. "Mismeasurement of Usual Hours Worked in the Census and ACS." *Economics Letters*, 102(1): 39–41.

Berson, Clémence. 2016. "Local Labor Markets and Taste-Based Discrimination." *IZA Journal of Labor Economics*, 5(1): , p. 5.

Black, Dan A. 1995. "Discrimination in an Equilibrium Search Model." *Journal of labor Economics*, 13(2): 309–334.

Black, Sandra E. 1999. "Do Better Schools Matter? Parental Valuation of Elementary Education." *The Quarterly Journal of Economics*, 114(2): 577–599.

Blair, Peter Q, and Bobby W Chung. 2018. "Job Market Signaling Through Occupational Licensing." URL: http://www.nber.org/papers/w24791.

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

Busso, Matias, Jesse Gregory, and Patrick Kline. 2013. "Assessing the Incidence and Efficiency of a Prominent Place Based Policy." *American Economic Review*, 103(2): 897–947.

Cai, Jing, and Morris M. Kleiner. 2016. "The Labor Market Consequences of Regulating Similar Occupations: The Licensing of Occupational and Physical Therapists." DOI: http://dx.doi.org/10.2139/ssrn.2802158.

Charrad, Malika, Nadia Ghazzali, Veronique Boiteau, Azam Niknafs, and Maintainer Malika Charrad. 2014. "Package 'nbclust'." *Journal of Statistical Software*, 61 1–36.

Correia, Sergio. 2018. "REGHDFE: Stata Module to Perform Linear or Instrumental-Variable Regression Absorbing Any Number of High-Dimensional Fixed Effects."

Cortes, Guido Matias, and Giovanni Gallipoli. 2018. "The Costs of Occupational Mobility: An Aggregate Analysis." *Journal of the European Economic Association*, 16(2): 275–315.

Cunningham, Evan. 2019. "Professional Certifications and Occupational Licenses." *Monthly Labor Review* 1–38.

DePasquale, Christina, and Kevin Stange. 2016. "Labor Supply Effects of Occupational Regulation: Evidence from the Nurse Licensure Compact."Technical report, National Bureau of Economic Research.

Dillender, Marcus, Anthony T Lo Sasso, Brian J Phelan, and Michael R Richards. 2022. "Occupational Licensing and the Healthcare Labor Market."Technical report, National Bureau of Economic Research.

Dodini, Samuel, Michael Lovenheim, Kjell Salvanes, and Alexander Willén. 2020. "Monopsony, Skills, and Labor Market Concentration."(DP15412): , URL: https://t.co/LUg2Z4qB6x?amp=1.

Dunn, Joseph C. 1974. "Well-separated Clusters and Optimal Fuzzy Partitions." *Journal of Cybernetics*, 4(1): 95–104.

Fanfani, Bernardo. 2018. "Tastes for Discrimination in Monopsonistic Labour Markets."Technical report.
Gittleman, Maury, Mark A Klee, and Morris M Kleiner. 2018. "Analyzing the Labor Market Outcomes of Occupational Licensing." *Industrial Relations: A Journal of Economy and Society*, 57(1): 57–100.
Halkidi, Maria, Michalis Vazirgiannis, and Yannis Batistakis. 2000. "Quality Scheme Assessment in the Clustering Process." In *European Conference on Principles of Data Mining and Knowledge Discovery.* 265–276, Springer.
Hirsch, Boris, and Elke J Jahn. 2015. "Is There Monopsonistic Discrimination Against Immigrants?" *ILR Review*, 68(3): 501–528.
Hirsch, Boris, Thorsten Schank, and Claus Schnabel. 2010. "Differences in Labor Supply to Monopsonistic Firms and the Gender Pay Gap: An Empirical Analysis Using Linked Employer-Employee Data from Germany." *Journal of Labor Economics*, 28(2): 291–330.
Hubert, Lawrence J, and Joel R Levin. 1976. "A General Statistical Framework for Assessing Categorical Clustering in Free Recall.." *Psychological Bulletin*, 83(6): , p. 1072.
Johnson, Janna E, and Morris M Kleiner. 2017. "Is Occupational Licensing a Barrier to Interstate Migration?." URL: http://www.nber.org/papers/w24107.
Kleiner, Morris M. 2000. "Occupational Licensing." *Journal of Economic Perspectives*, DOI: http://dx.doi.org/10.1257/jep.14.4.189.
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): , DOI: http://dx.doi.org/10.1086/669060.
Kleiner, Morris M, Allison Marier, Kyoung Won Park, and Coady Wing. 2016. "Relaxing Occupational Licensing Requirements: Analyzing Wages and Prices for a Medical Service." *The Journal of Law and Economics*, 59(2): 261–291.
Kleiner, Morris M, and Kyoung Won Park. 2010. "Battles Among Licensed Occupations: Analyzing Government Regulations on Labor Market Outcomes for Dentists and Hygienists."Technical report, National Bureau of Economic Research.
Kleiner, Morris M, and Evan J Soltas. 2019. "A Welfare Analysis of Occupational Licensing in US States."(26283): .
Kleiner, Morris M., and Evgeny Vorotnikov. 2017. "Analyzing Occupational Licensing Among the States." *Journal of Regulatory Economics*, DOI: http://dx.doi.org/10.1007/s11149-017-9333-y.
Kleiner, Morris, and Ming Xu. 2020. "Occupational Licensing and Labor Market Fluidity."
Koumenta, Maria, Amy Humphris, Morris Kleiner, and Mario Pagliero. 2014. "Occupational Regulation in the EU and UK: Prevalence and Labour Market Impacts." *Final Report, Department for Business, Innovation and Skills, School of Business and Management, Queen Mary University of London, London.*
Koumenta, Maria, and Mario Pagliero. 2019. "Occupational Regulation in the European Union: Coverage and Wage Effects." *British Journal of Industrial Relations*, 57(4): 818–849.
Kugler, Adriana D, and Robert M Sauer. 2005. "Doctors Without Borders? Relicensing Requirements and Negative Selection in the Market for Physicians." *Journal of Labor Economics*, 23(3): 437–465.
Lipsitz, Michael, and Evan Starr. 2022. "Low-Wage Workers and the Enforceability of Noncompete Agreements." *Management Science*, Forthcoming, URL: https://doi.org/10.1287/mnsc.2020.3918, DOI: http://dx.doi.org/10.1287/mnsc.2020.3918.
Lipsius, Ben. 2018. "Labor Market Concentration Does Not Explain the Falling Labor Share." *Available at SSRN 3279007.*
Marinescu, Ioana Elena, Ivan Ouss, and Louis-Daniel Pape. 2019. "Wages, Hires, and Labor Market Concentration." *Available at SSRN 3453855.*
Mincer, Jacob. 1974. "Schooling, Experience, and Earnings."
Pizzola, Brandon, and Alexander Tabarrok. 2017. "Occupational Licensing Causes a Wage Premium: Evidence from a Natural Experiment in Colorado's Funeral Services Industry." *International Review of Law and Economics*, 50 50–59.
Qiu, Yue, and Aaron Sojourner. 2019. "Labor Market Concentration and Labor Compensation." *Available at SSRN 3312197.*
Ransom, Michael R, and Val E Lambson. 2011. "Monopsony, Mobility, and Sex Differences in Pay: Missouri School Teachers." *American Economic Review*, 101(3): 454–59.
Ransom, Michael R, and Ronald L Oaxaca. 2010. "New Market Power Models and Sex Differences in Pay." *Journal of Labor Economics*, 28(2): 267–289.
Ransom, Tyler. 2021. "Labor Market Frictions and Moving Costs of the Employed and Unemployed."

Journal of Human Resources 0219–10013R2.

Redbird, Beth. 2016. "Northwestern Licensing Database: Version 2016."

Redbird, Beth. 2017. "The New Closed Shop? The Economic and Structural Effects of Occupational Licensure." *American Sociological Review*, DOI: http://dx.doi.org/10.1177/0003122417706463.

Rinz, Kevin. 2018. "Labor Market Concentration, Earnings Inequality, and Earnings Mobility." *Center for Administrative Records Research and Applications Working Paper*, 10.

Robinson, Joan. 1933. *The Economics of Imperfect Competition.*: Macmillan.

Rousseeuw, Peter J. 1987. "Silhouettes: A Graphical Aid to the Interpretation and Validation of Cluster Analysis." *Journal of Computational and Applied Mathematics*, 20 53–65.

Rumbaut, Rubén G, and Douglas S Massey. 2013. "Immigration & Language Diversity in the United States." *Daedalus*, 142(3): 141–154.

Schubert, Gregor, Anna Stansbury, and Bledi Taska. 2019. "Mitigating Monopsony: Occupational Mobility and Outside Options."

Shaw, Kathryn L. 1987. "Occupational Change, Employer Change, and the Transferability of Skills." *Southern Economic Journal* 702–719.

Sokal, RR, and CD Michener. 1958. "A Statistical Method for Evaluating Systematic Relationships."

Starr, Evan. 2019. "Consider This: Training, Wages, and the Enforceability of Covenants Not to Compete." *ILR Review*, 72(4): 783–817.

Starr, Evan, Justin Frake, and Rajshree Agarwal. 2019. "Mobility Constraint Externalities." *Organization Science*, 30(5): 961–980.

Starr, Evan P., J.J. Prescott, and Norman D. Bishara. 2021. "Noncompete Agreements in the US Labor Force." *The Journal of Law and Economics*, 64(1): 53–84, URL: https://doi.org/10.1086/712206, DOI: http://dx.doi.org/10.1086/712206.

Steven, Ruggles, Sarah Flood, Ronald Goeken, Josiah Grover, Erin Meyer, Jose Pacas, and Matthew Sobek. 2019. "IPUMS USA: Version 9.0." DOI: http://dx.doi.org/https://doi.org/10.18128/D010.V9.0.

Thornton, Robert J, and Edward J Timmons. 2013. "Licensing One of the World's Oldest Professions: Massage." *The Journal of Law and Economics*, 56(2): 371–388.

Vargo, Emily, Ethan Bayne, and Edward Timmons. 2020. "Occupational Regulation Database. April 2020 version [dataset]." URL: https://csorsfu.com/find-occupations/.

Webber, Douglas A. 2015. "Firm Market Power and the Earnings Distribution." *Labour Economics*, 35 123–134.

Webber, Douglas A. 2016. "Firm-Level Monopsony and the Gender Pay Gap." *Industrial Relations: A Journal of Economy and Society*, 55(2): 323–345.

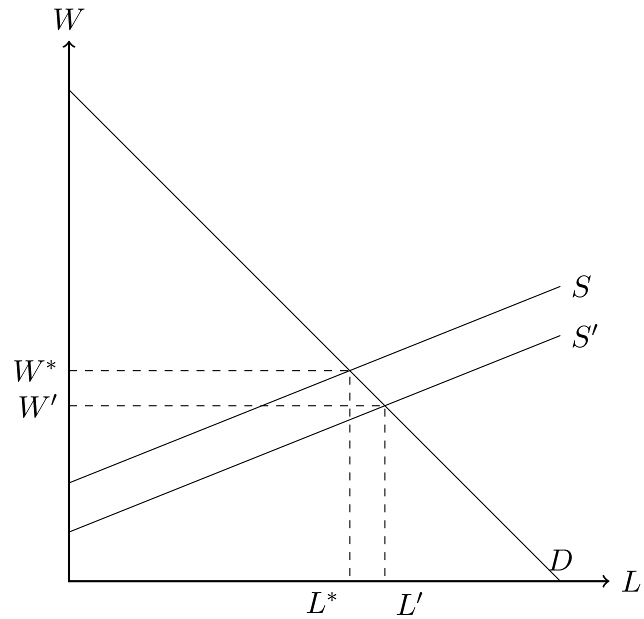
Wing, Coady, and Allison Marier. 2014. "Effects of Occupational Regulations on the Cost of Dental Services: Evidence from Dental Insurance Claims." *Journal of Health Economics*, 34 131–143.

Yeung, Ka Yee, and Walter L. Ruzzo. 2001. "Principal Component Analysis for Clustering Gene Expression Data." *Bioinformatics*, 17(9): 763–774.

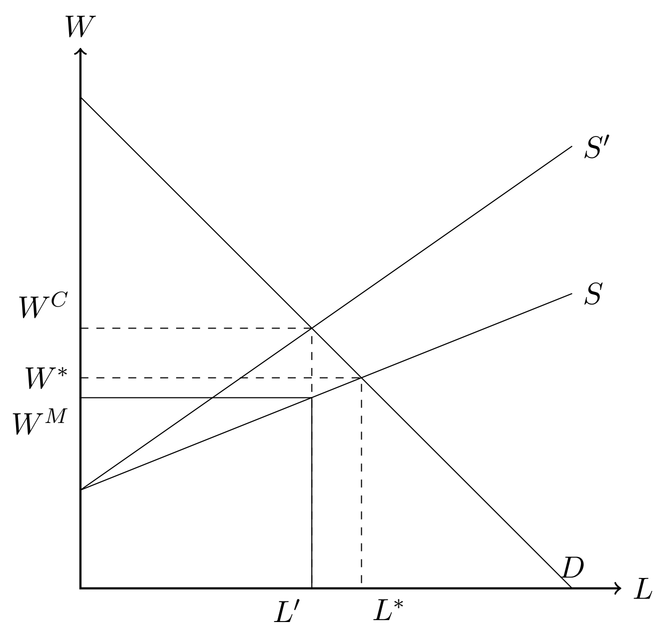
Figures

Figure 1: Competitive vs Monopsonistic Labor Market

Panel A: Competitive Market Labor Supply Shift

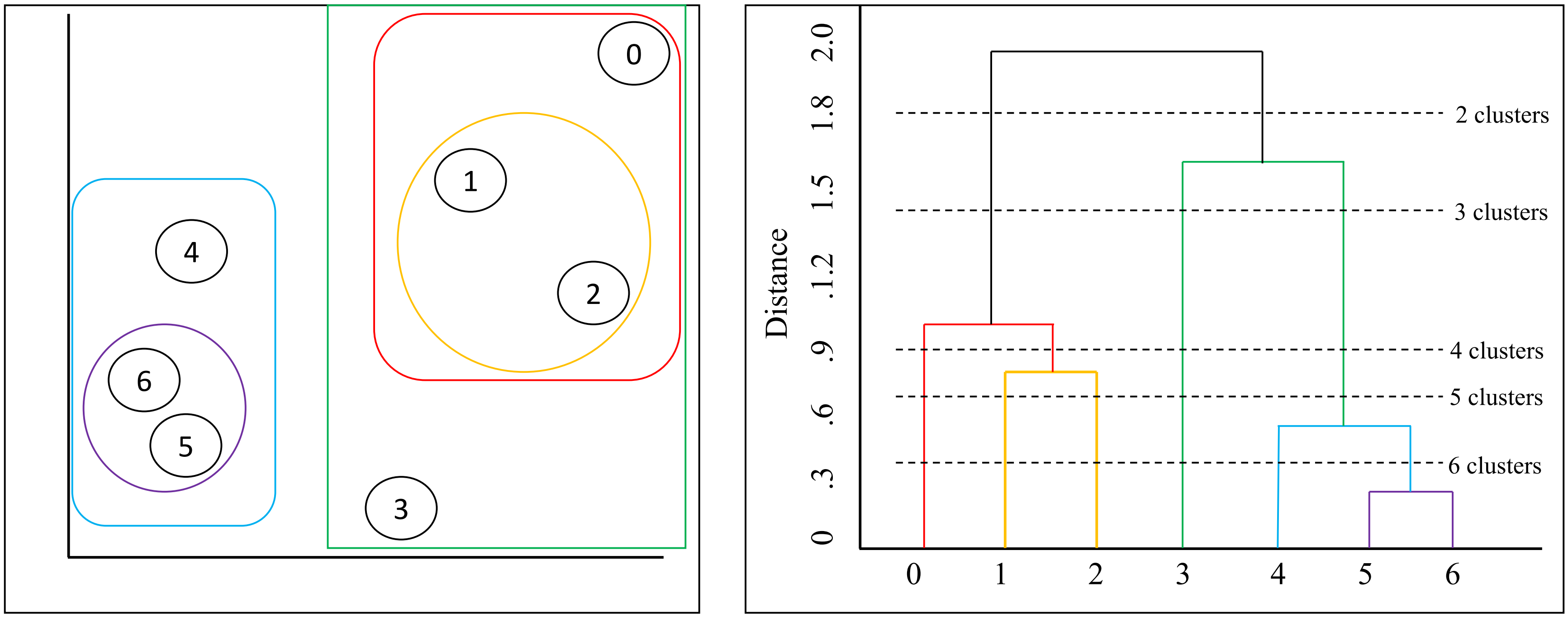


Panel B: Monopsony Model



Notes: An illustration of the possible spillover effects of occupational licensure onto other occupations in a labor supply (competitive) model vs a monopsony model.

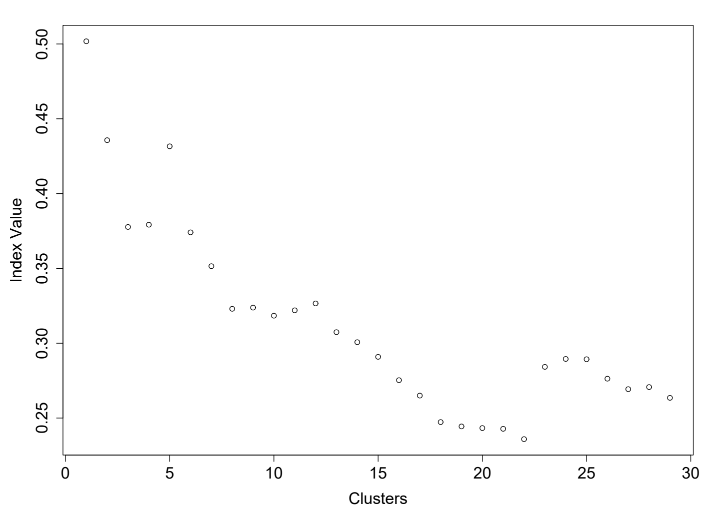
Figure 2: Hierarchical Agglomerative Clustering Example



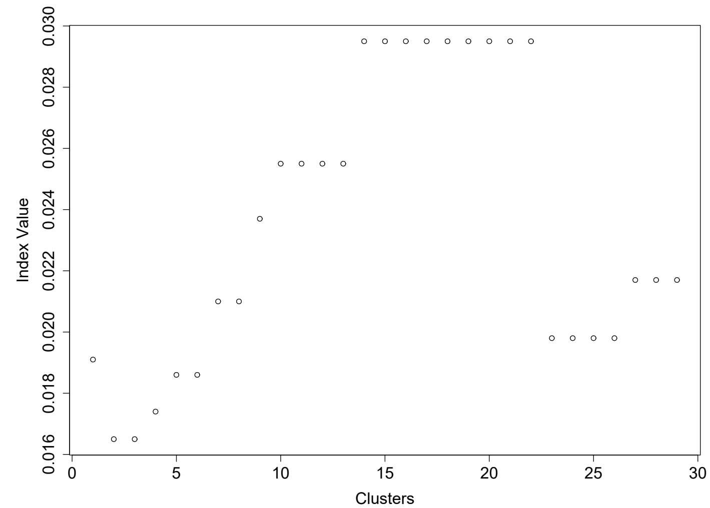
Note: Moving up the dendrogram, clusters are sequentially merged. The researcher can then choose cut points at a certain number of clusters or at a maximum distance value within clusters. First, groups 5 and 6 merge to form the purple cluster. Next, this purple cluster merges with group 4 to form the blue cluster. Next, groups 1 and 2 merge to form the yellow cluster. Then group 0 merges with the yellow cluster to form the red cluster. Finally, group 3 is merged with the blue cluster to form a green cluster.

Figure 3: Cluster Validation Exercises

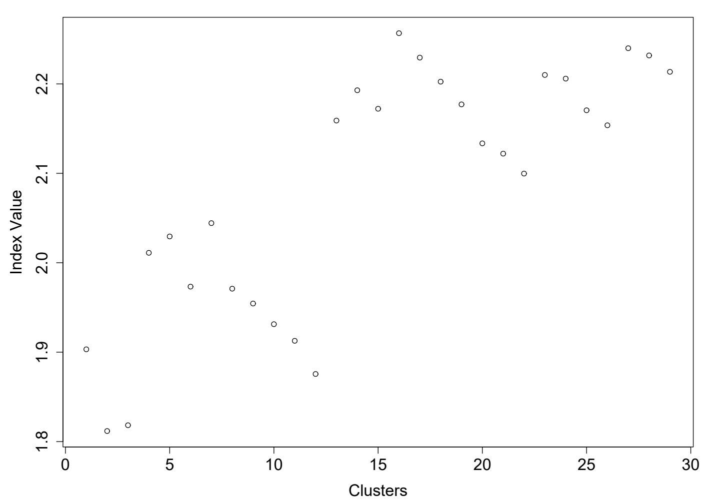
Panel A: Sillhouette (Maximization)



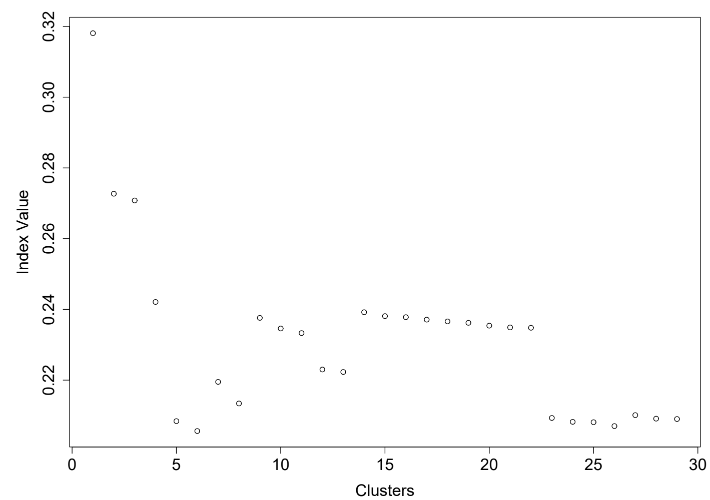
Panel B: Dunn's Index (Maximization)



Panel C: SD Index (Minimization)

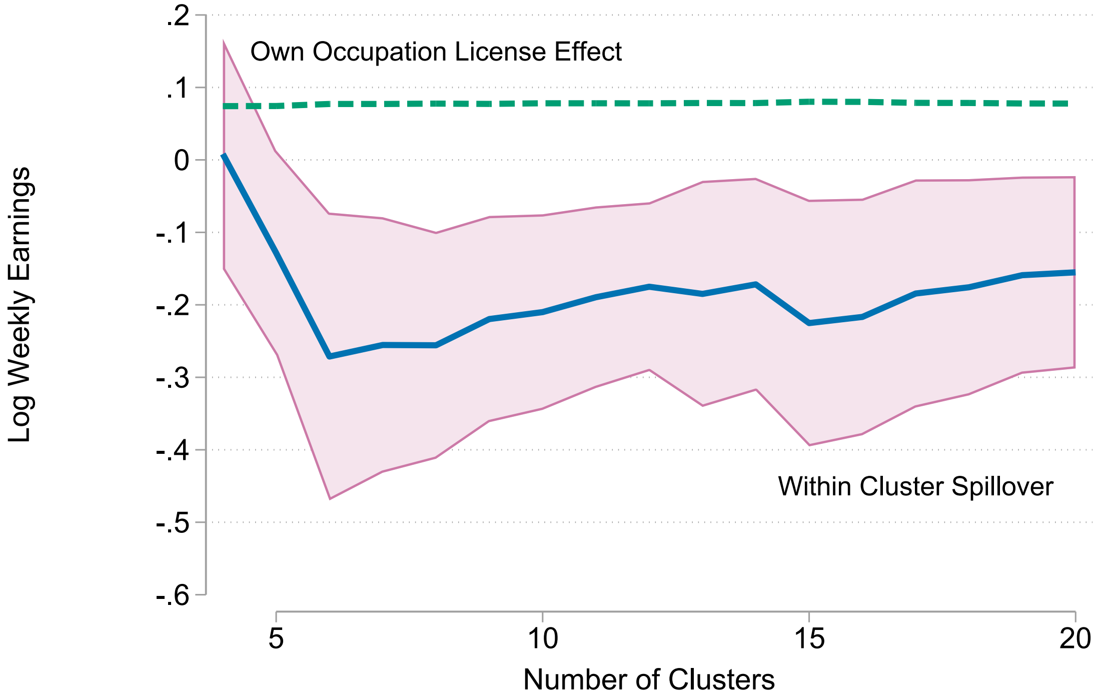


Panel D: C Index (Minimization)



Source: Author's calculations of O*NET skills data following six skills in Acemoglu and Autor (2011) and median log wage.
Note: Clusters are generated using the HAC approach detailed in section 4.1.

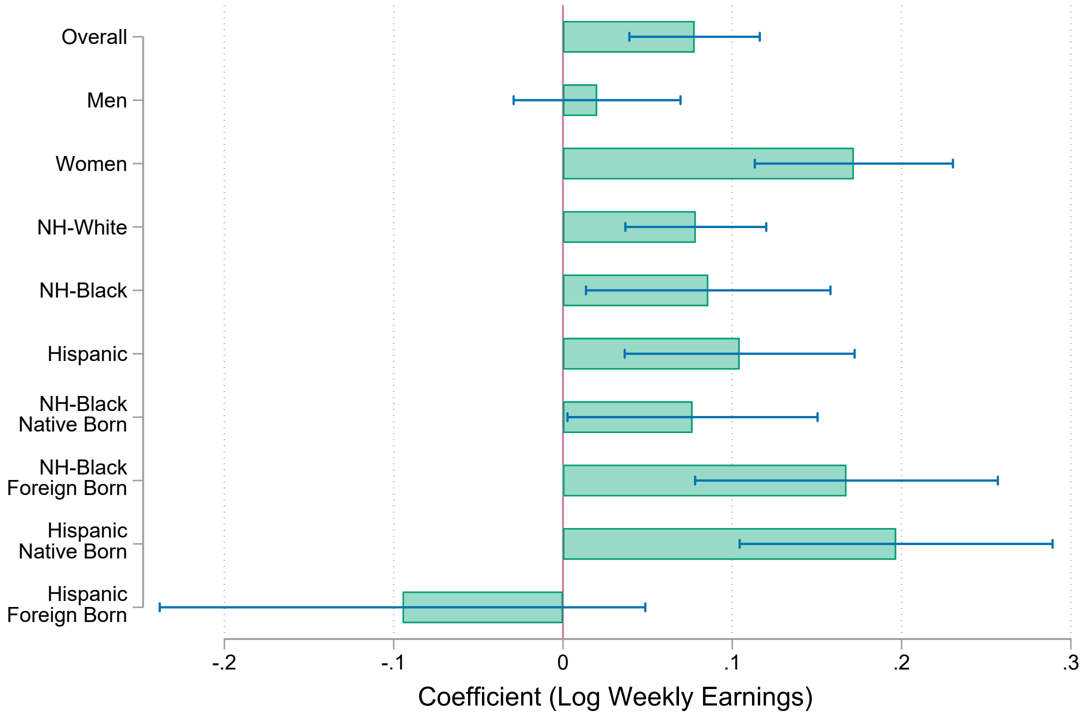
Figure 4: Coefficients of Log Weekly Earnings by Number of Clusters



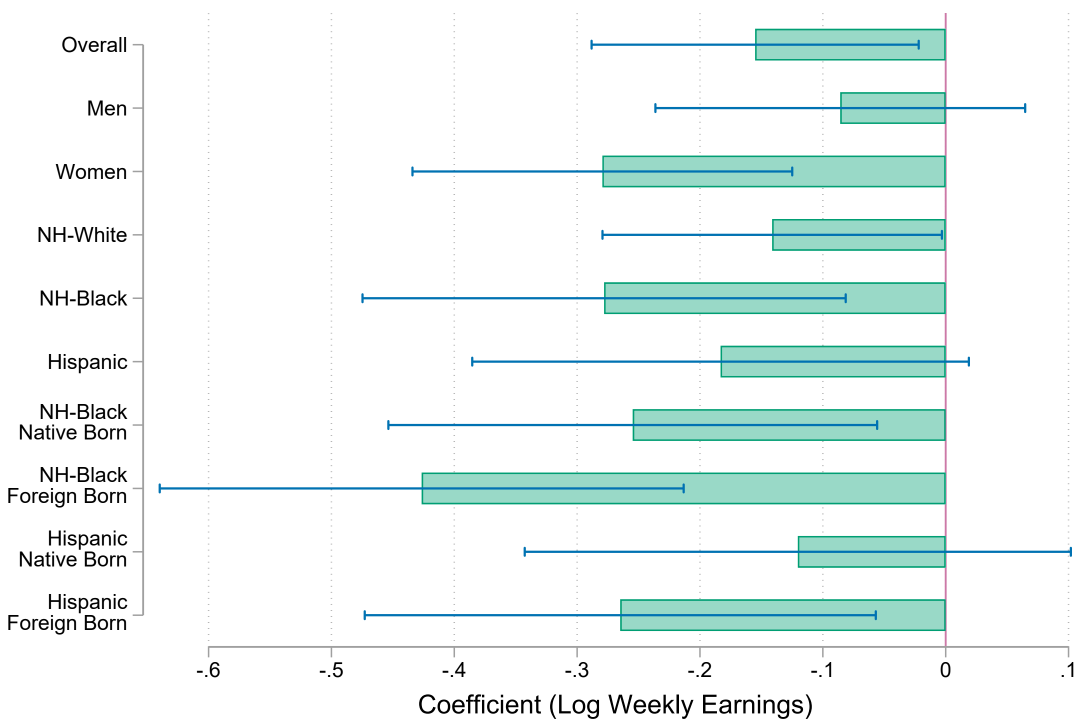
Source: Author's calculations of ACS, O*NET, and CPS licensing data.
Note: Coefficients are generated from the border match design detailed in Equation 3. Standard errors are clustered at the occupation level. 95% confidence intervals in red. Spillover coefficients are based on 100% licensure of an occupation's cluster outside their own occupation.

Figure 5: Coefficients of Log Weekly Earnings by Subgroup at 20 Clusters

Panel A: Own Earnings Effects



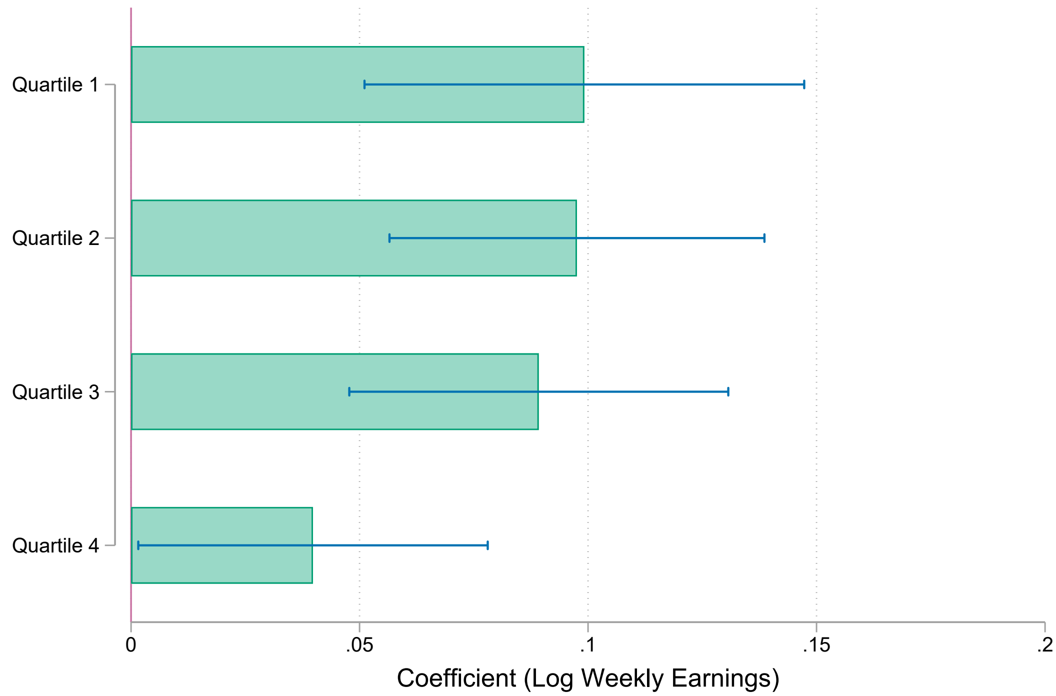
Panel B: Within-Cluster Spillover Effects



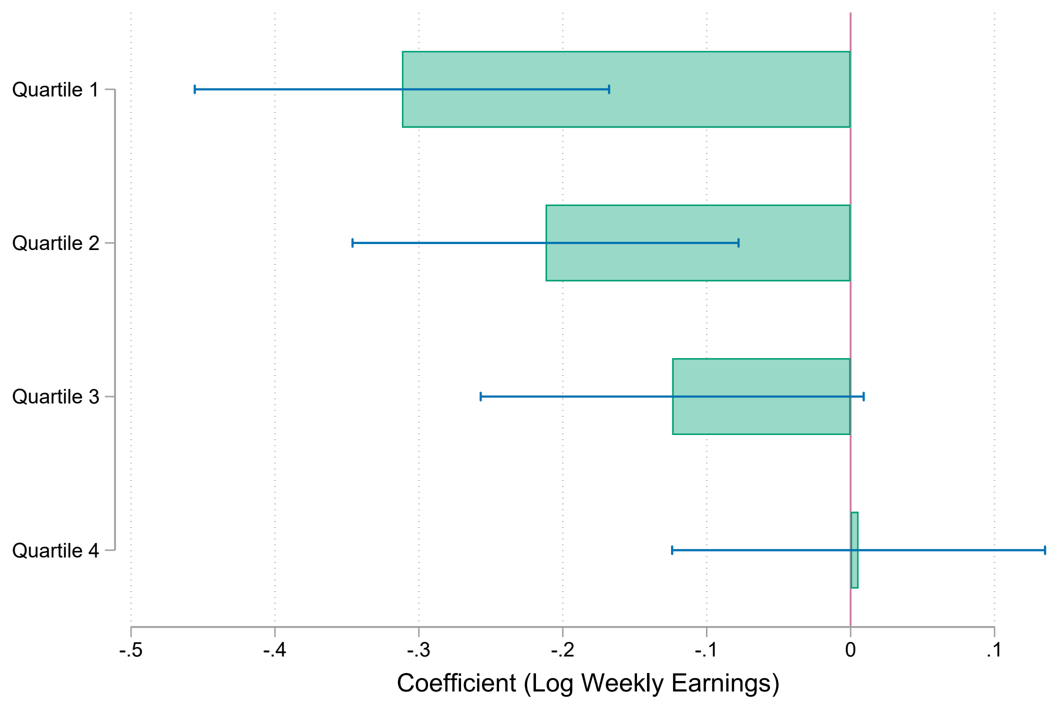
Source: Author's calculations of ACS, O*NET, and CPS licensing data.
Note: Coefficients are generated from the border match design detailed in Equation 3 using 20 skill clusters. Bars represent point estimates, and the bands represent the 95% confidence interval clustered at the occupation level. Spillover coefficients are based on 100% licensure of an occupation's cluster outside their own occupation.

Figure 6: Coefficients of Log Weekly Earnings by Labor Market Size at 20 Clusters

Panel A: Own Earnings Effects

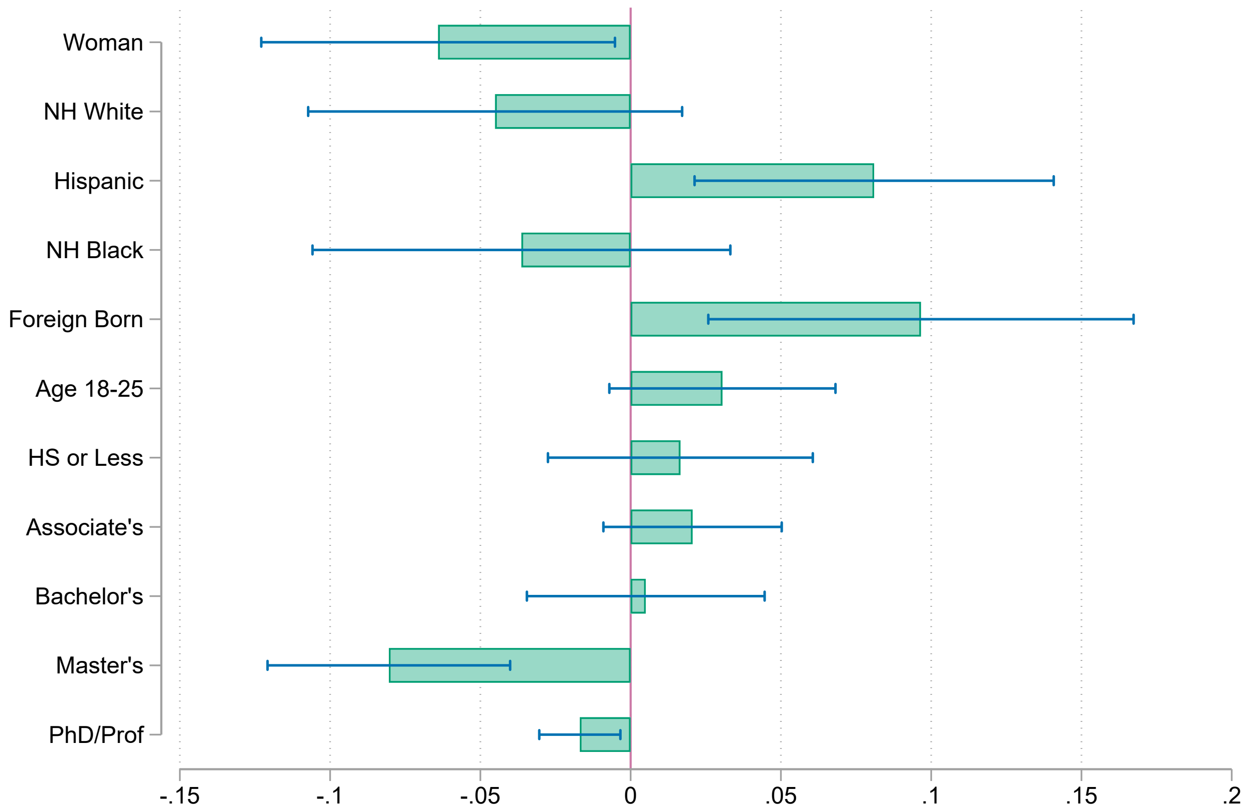


Panel B: Within-Cluster Spillover Effects



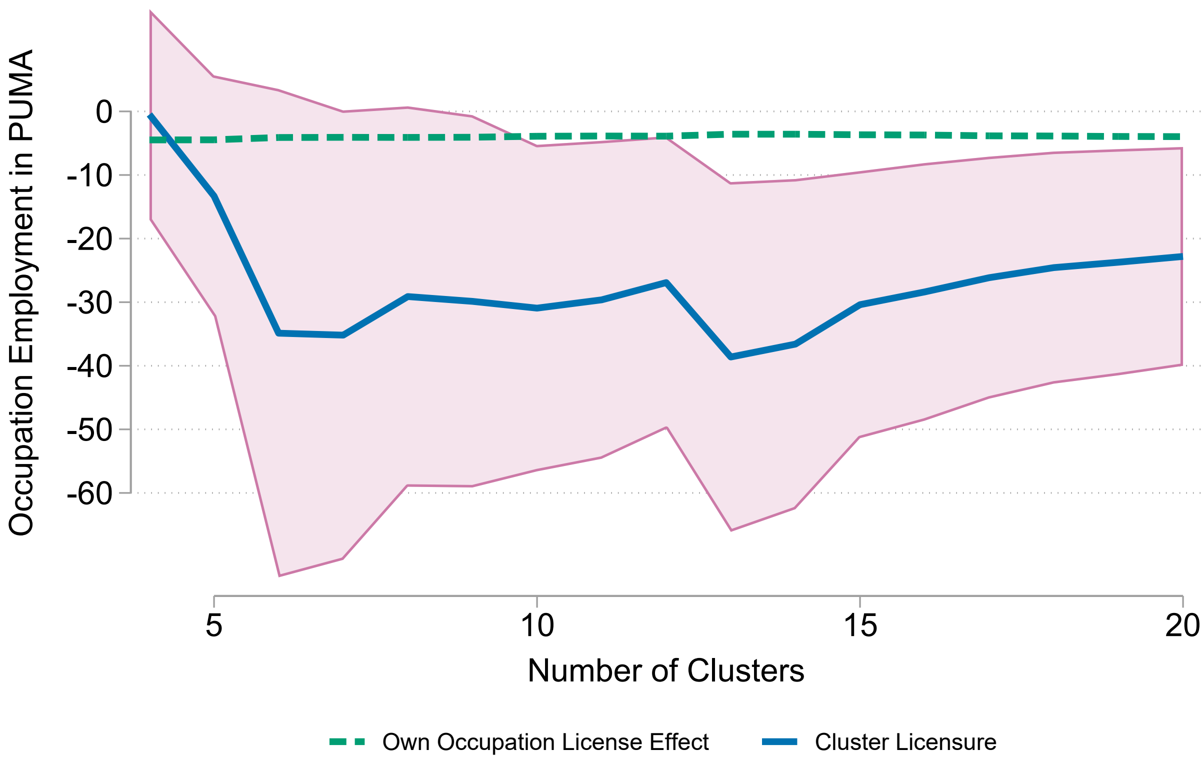
Source: Author's calculations of ACS, O*NET, and CPS licensing data.
Note: Coefficients are generated from the border match design detailed in Equation 3 using 20 skill clusters. Bars represent point estimates, and the bands represent the 95% confidence interval clustered at the occupation level. Spillover coefficients are based on 100% licensure of an occupation's cluster outside their own occupation. Quartiles are defined by the size of the population age 18-64 within each PUMA.

Figure 7: Composition Effects of Licensing Spillovers, 20 Clusters



Source: Author's calculations of ACS, O*NET, and CPS licensing data.
Note: Coefficients are generated from the border match design detailed in Equation 3 for linear probability models on binary outcomes. Bars represent point estimates, and the bands represent the 95% confidence interval clustered at the occupation level. Spillover coefficients are based on 100% licensure of an occupation's cluster outside their own occupation for 20 total defined clusters.

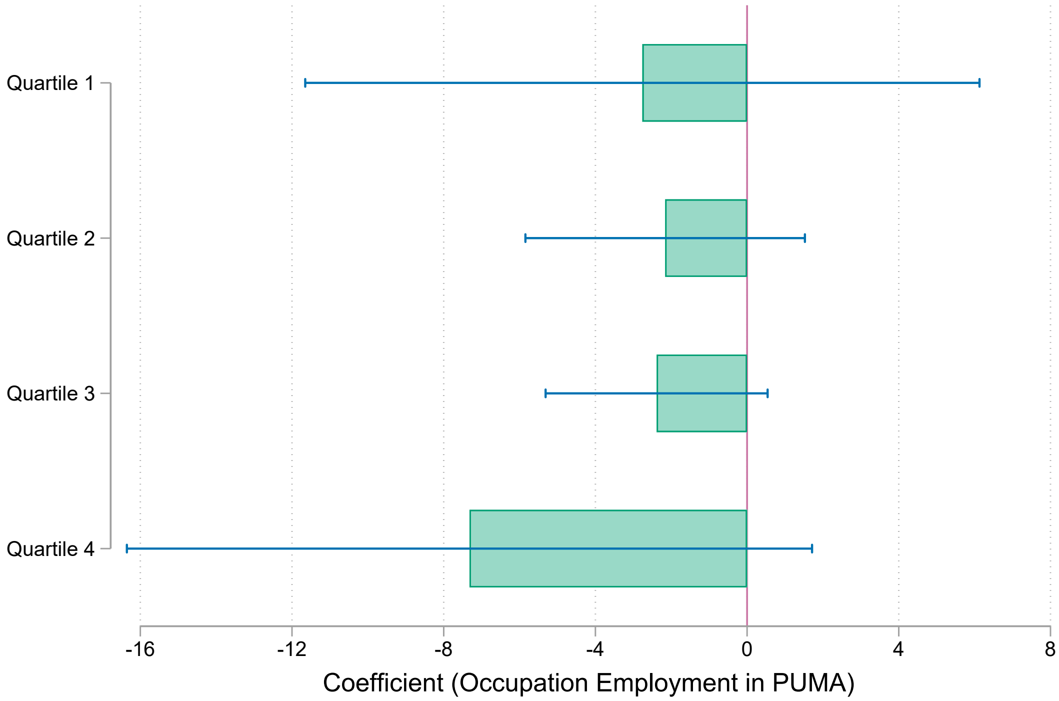
Figure 8: Employment Effects of Licensing Spillovers by Number of Clusters



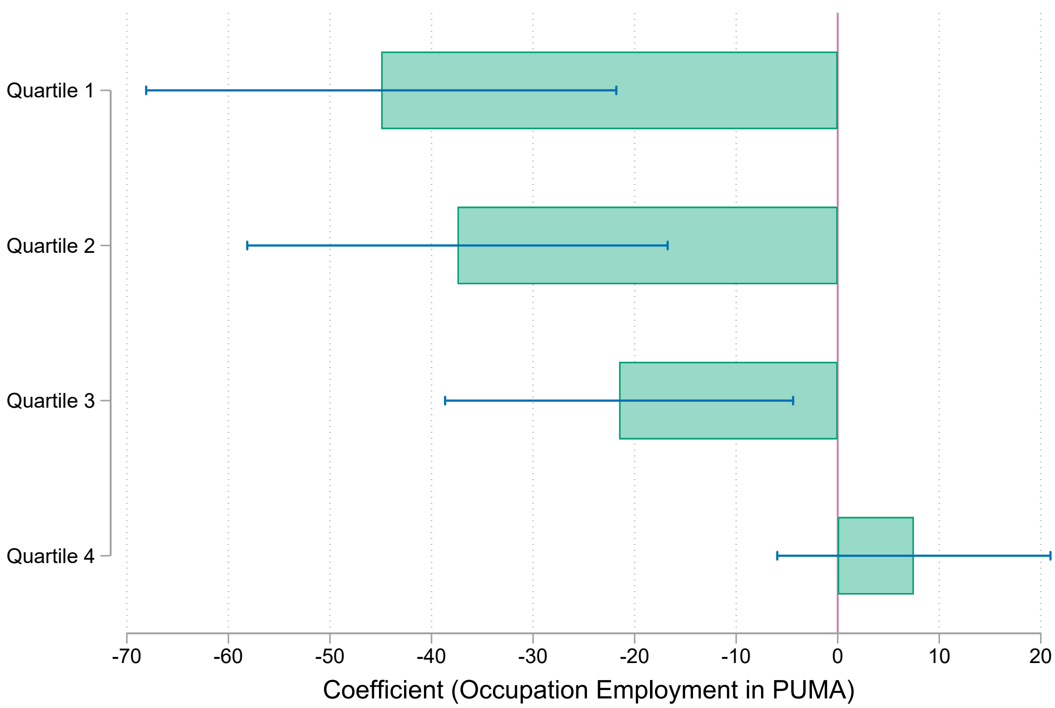
Source: Author's calculations of ACS, O*NET, and CPS licensing data.
Note: Coefficients are generated from the border match design detailed in Equation 3. Standard errors are clustered at the occupation level. 95% confidence intervals in red. Spillover coefficients are based on 100% licensure of an occupation's cluster outside their own occupation.

Figure 9: Coefficients of Employment by Labor Market Size at 20 Clusters

Panel A: Own Employment Effects

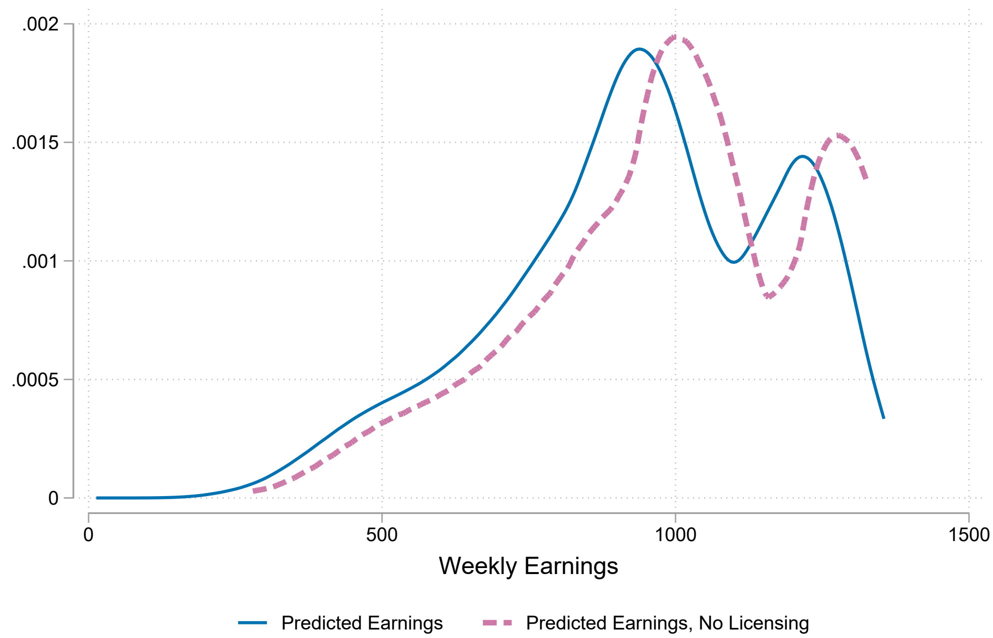


Panel B: Within-Cluster Spillover Effects



Source: Author's calculations of ACS, O*NET, and CPS licensing data.
Note: Coefficients are generated from the border match design detailed in Equation 3 using 20 skill clusters. Bars represent point estimates, and the bands represent the 95% confidence interval clustered at the occupation level. Spillover coefficients are based on 100% licensure of an occupation's cluster outside their own occupation. Quartiles are defined by the size of the population age 18-64 within each PUMA.

Figure 10: Kernel Density of the Counterfactual Distribution of Weekly Earnings
Panel A: Kernel Density of Predicted Earnings

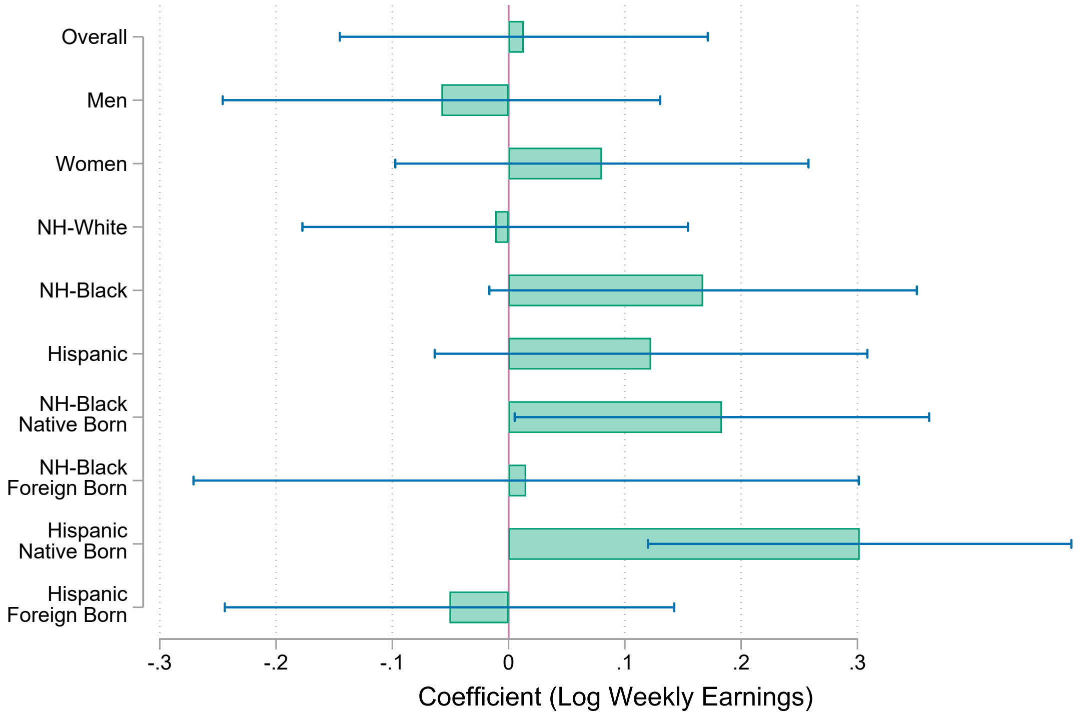


Panel B: Difference in Densities

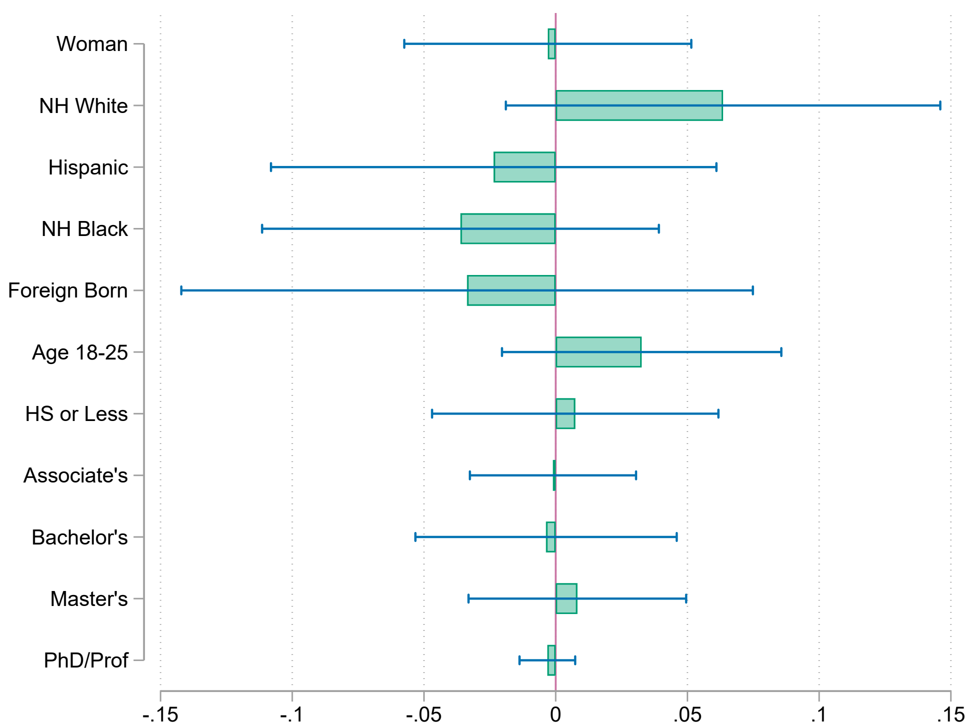
Source: Author's calculations of ACS, O*NET, and CPS licensing data.
Note: Coefficients are generated from the border match design detailed in Equation 3 using 20 skill clusters. The model includes fixed effects for occupation, border pair, and state. Predicted earnings are for the status quo and for setting licensing rates to zero for one's own occupation and skill cluster.

Figure 11: Spillover Coefficients of Log Weekly Earnings, 20 Placebo Clusters

Panel A: Earnings Effects

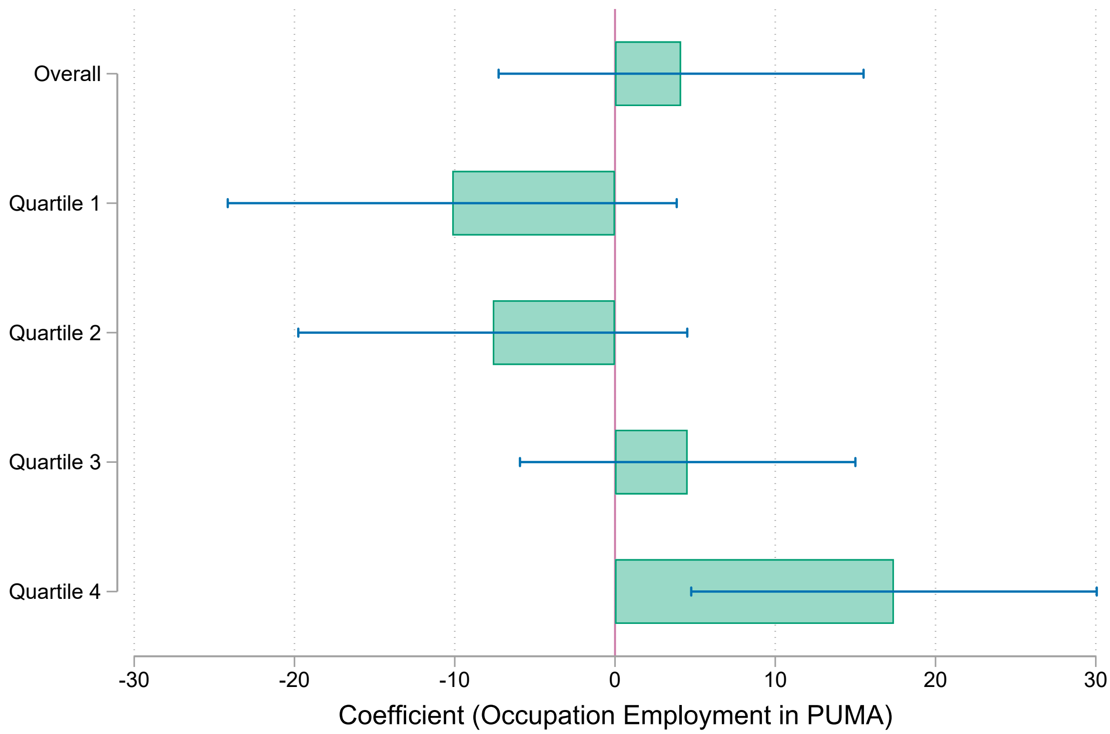


Panel B: Composition Effects



Source: Author's calculations of ACS, O*NET, and CPS licensing data.
Note: Coefficients are generated from the border match design detailed in Equation 3 using 20 placebo skill clusters. Bars represent point estimates, and the bands represent the 95% confidence interval clustered at the occupation level. Spillover coefficients are based on 100% licensure of an occupation's cluster outside their own occupation.

Figure 12: Coefficients of Employment by Labor Market Size at 20 Placebo Clusters



Source: Author's calculations of ACS, O*NET, and CPS licensing data.
Note: Coefficients are generated from the border match design detailed in Equation 3 using 20 placebo skill clusters. Bars represent point estimates, and the bands represent the 95% confidence interval clustered at the occupation level. Spillover coefficients are based on 100% licensure of an occupation's cluster outside their own occupation. Quartiles are defined by the size of the population age 18-64 within each PUMA.

Tables

Table 1: Summary Statistics by Sample

	Border Sample		Full Sample	
	Mean	SD	Mean	SD
Log Weekly Earnings	6.51	0.83	6.55	0.85
Female	0.47	0.50	0.47	0.50
NH-White	0.74	0.44	0.62	0.49
NH-Black	0.11	0.31	0.12	0.32
Hispanic	0.10	0.30	0.18	0.38
Asian/Pacific Islander	0.03	0.17	0.06	0.23
Foreign Born	0.11	0.32	0.19	0.39
Age	40.48	12.95	40.04	12.80
High School/Less	0.37	0.48	0.34	0.47
Associate's Degree	0.09	0.29	0.09	0.28
Bachelor's Degree	0.19	0.40	0.22	0.41
Master's Degree	0.08	0.28	0.09	0.29
PhD/Professional Degree	0.02	0.13	0.02	0.14
Share Own Occupation Licensed	0.18	0.19	0.17	0.18
Share Cluster Licensed Outside Focal Occ.	0.21	0.11	0.21	0.11
N	1,337,103		4,578,382	
PUMAs	244		982	
Occupations	410		410	
Border Pairs	110		N/A	

Source: Author's calculations of ACS, CPS, and O*NET data.
Notes: Clusters are based on description in Section 4.1. ACS samples are from 2014-2017 corresponding with CPS individual licensing data from 2015-2018.

Table 2: Components of Latent Skill Measurements

Occupational Skill Area	O*NET Variables
Non-Routine, Cognitive, Analytical	“Analyzing data/information” “Thinking creatively” “Interpreting information for others”
Non-Routine, Cognitive, Interpersonal	“Establishing and maintaining personal relationships” “Guiding, directing and motivating subordinates” “Coaching/developing others”
Non-Routine, Manual, Physical Adaptability	“Operating vehicles, mechanized devices, or equipment” “Spend time using hands to handle, control or feel objects, tools or controls” “Manual dexterity” “Spatial orientation”
Routine, Cognitive	“Importance of repeating the same tasks” “Importance of being exact or accurate” “Structured v. Unstructured work (reverse)”
Routine, Manual	“Pace determined by speed of equipment” “Controlling machines and processes” “Spend time making repetitive motions”
Non-Routine, Interpersonal Adaptability	“Social Perceptiveness”

Source: Version 22.0 of the O*NET database (2017) and Acemoglu and Autor (2011).

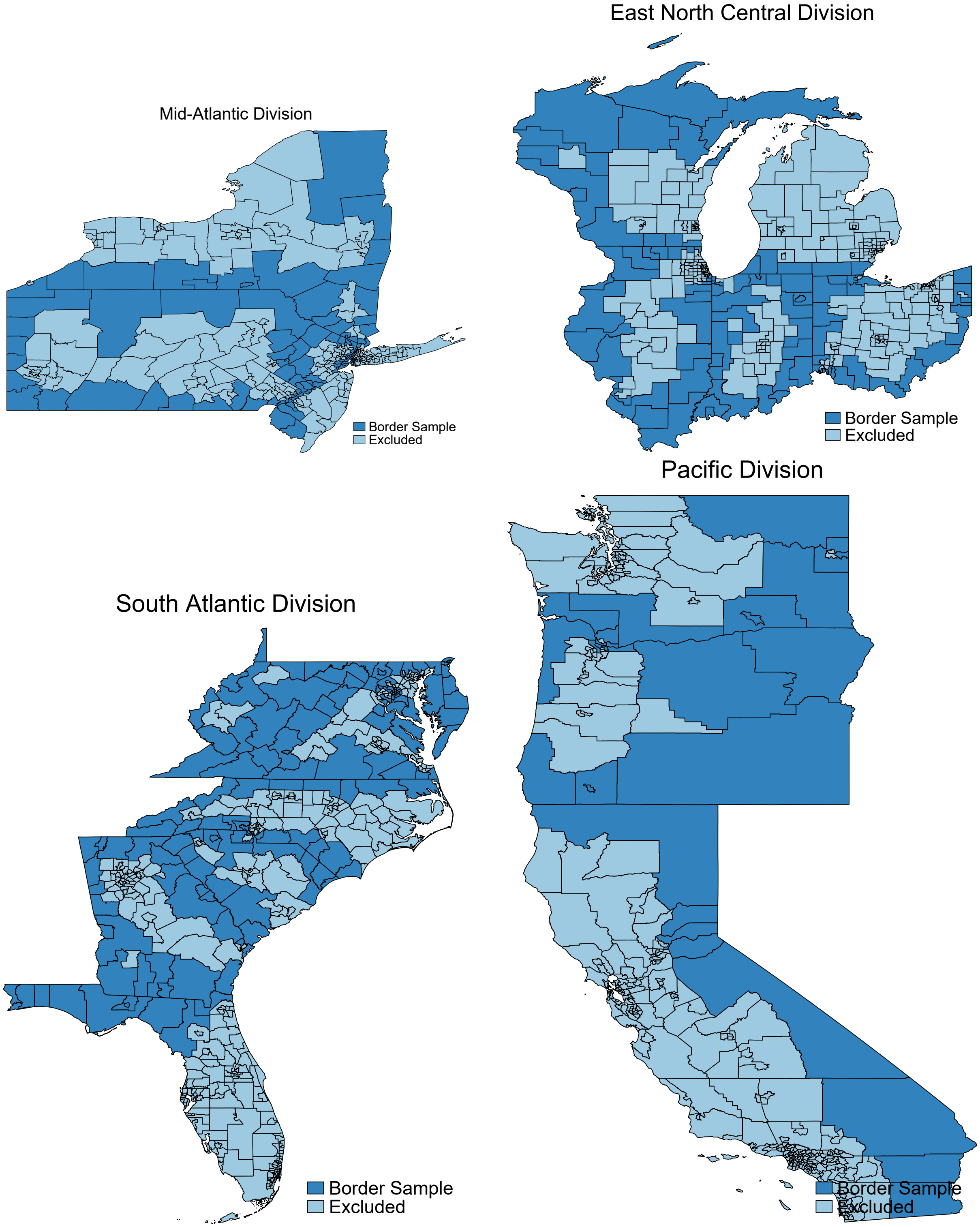
Table 3: Distributional Statistics of Predicted Weekly Earnings with vs without Licensing

	Status Quo	Without Licensing	Percent Change
Ratio 90/10	2.062	1.982	-3.88%
Ratio 90/50	1.312	1.279	-2.52%
Ratio 10/50	0.636	0.645	1.42%
Ratio 75/25	1.438	1.394	-3.06%
Gini Coefficient	0.144	0.134	-6.82%

Source: Author's calculations of ACS, CPS, and O*NET data.
Notes: Distributional statistics are based on the predictions from Equation 3 as described in Section 5.4.

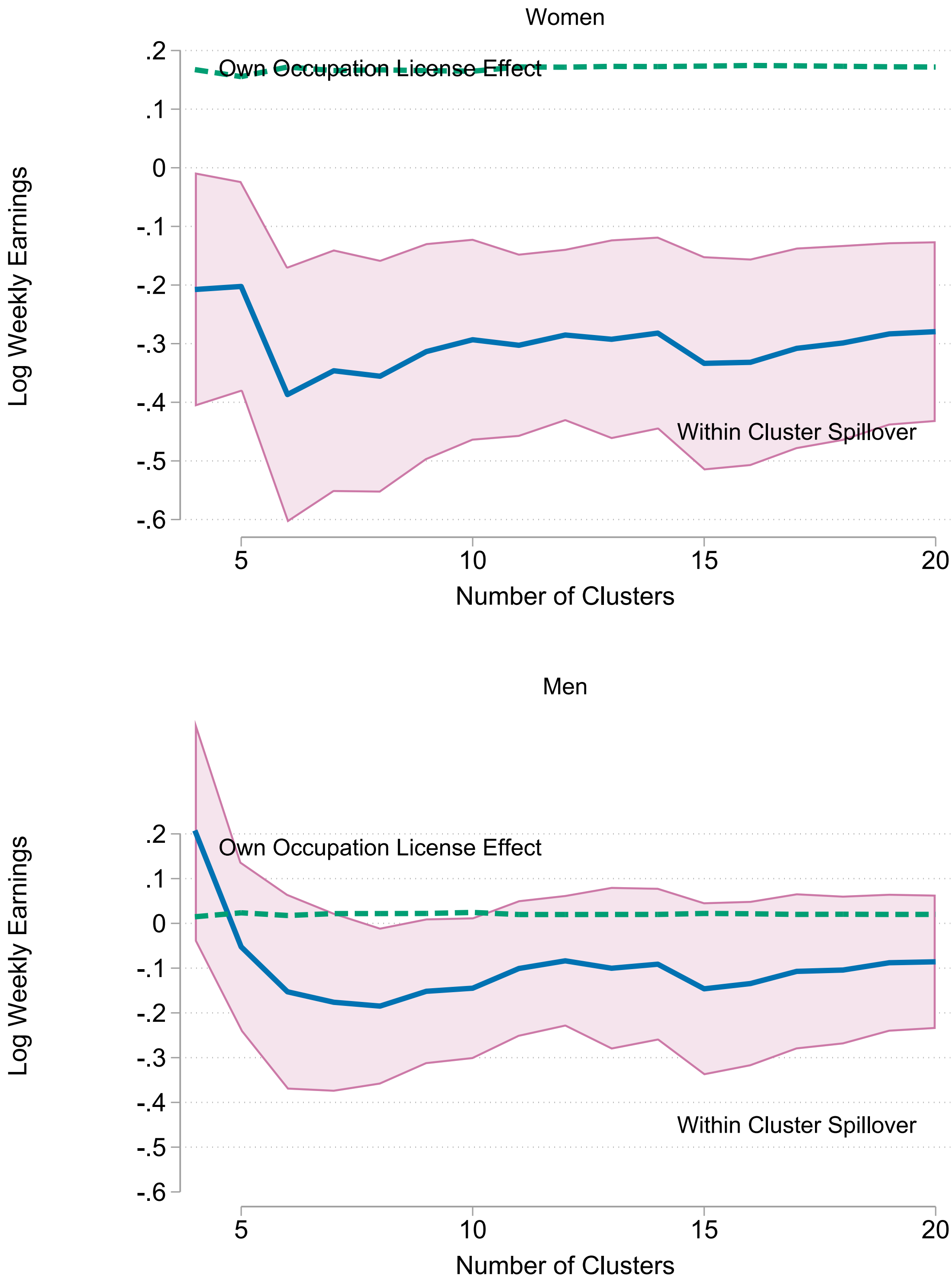
A Figures and Tables Appendix

Figure A1: Border Sample PUMAs in Select Census Divisions



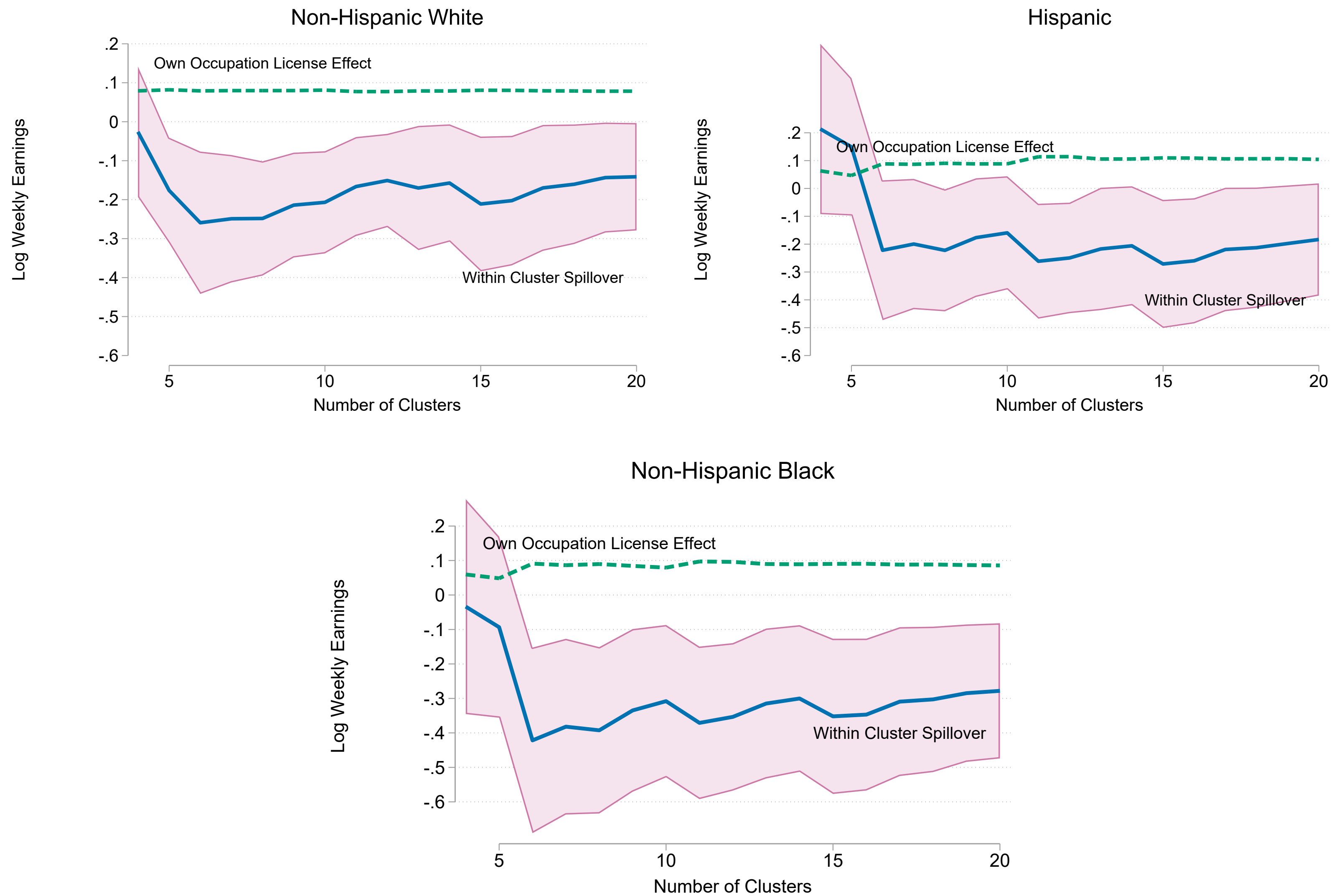
Source: Author's border sample of ACS Public Usa Microdata Areas (PUMAs)

Figure A2: Coefficients of Log Weekly Earnings by Number of Clusters, by Gender



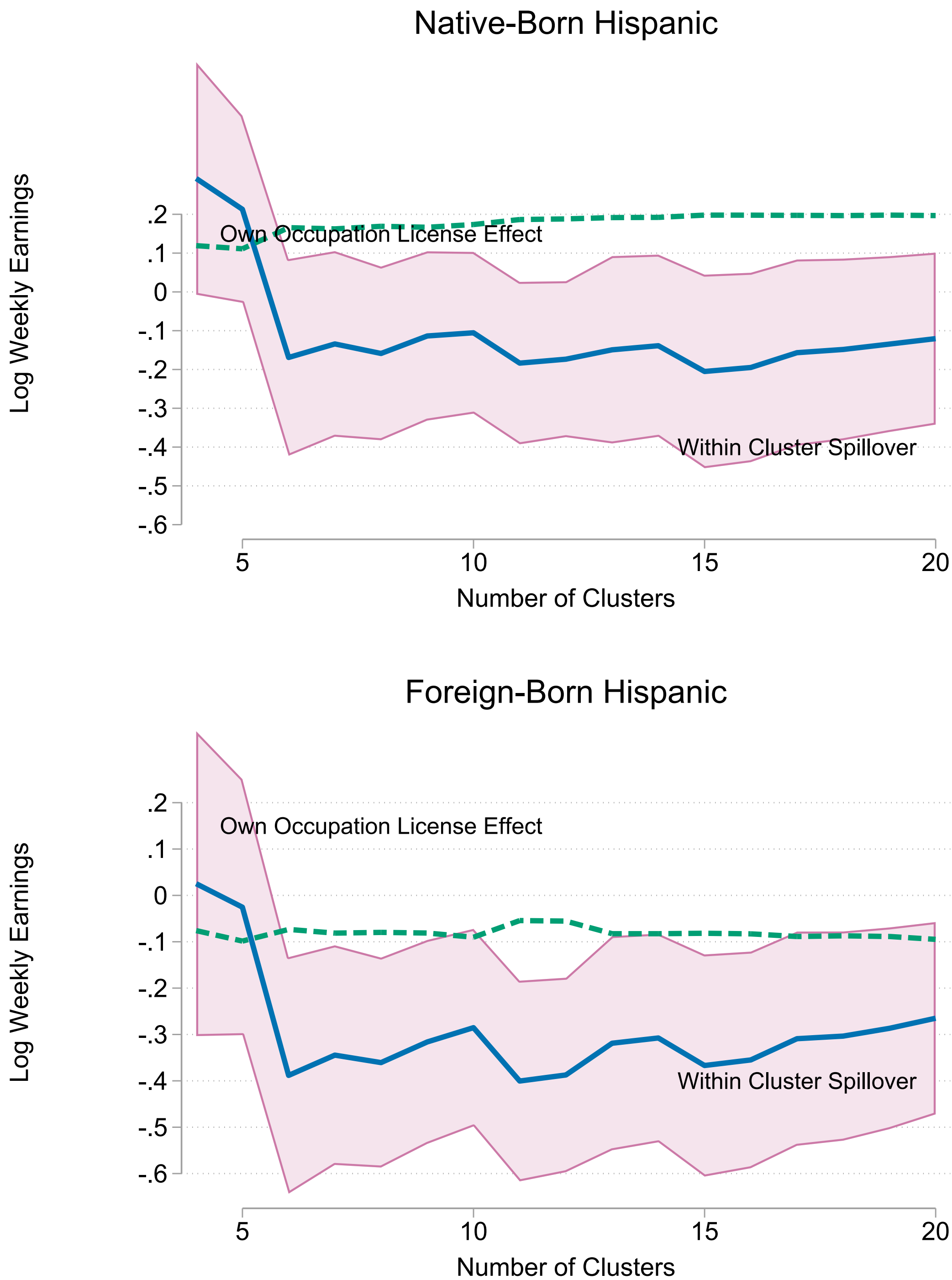
Source: Author's calculations of ACS, O*NET, and CPS licensing data.
Note: Coefficients are generated from the border match design detailed in Equation 3. Standard errors are clustered at the occupation level. 95% confidence intervals in red. Spillover coefficients are based on 100% licensure of an occupation's cluster outside their own occupation.

Figure A3: Coefficients of Log Weekly Earnings by Number of Clusters, by Race/Ethnicity



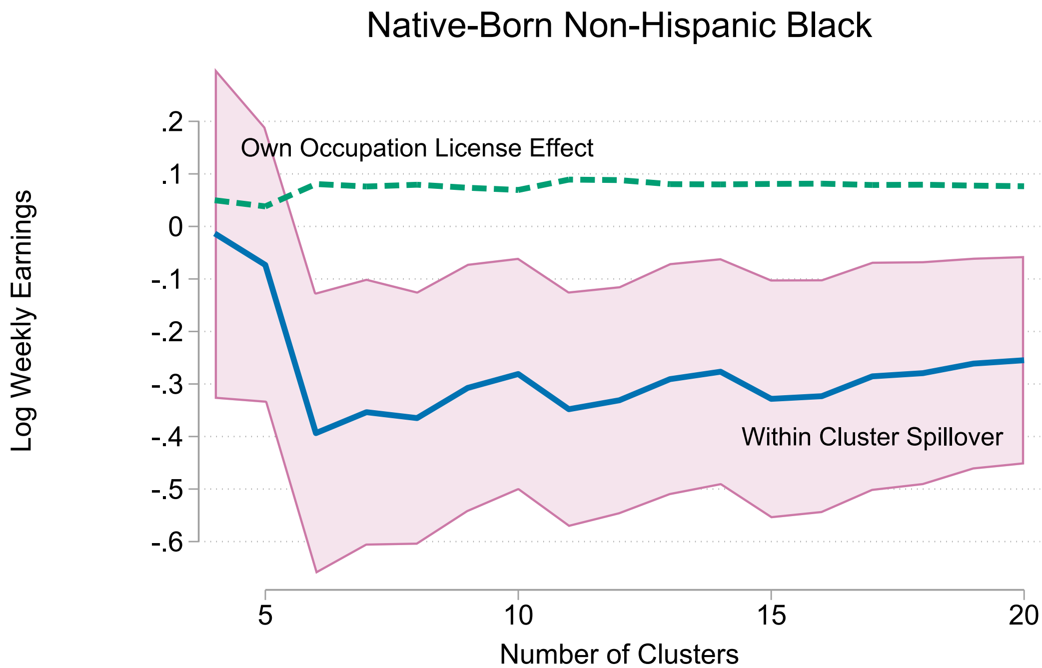
Source: Author's calculations of ACS, O*NET, and CPS licensing data.
Note: Coefficients are generated from the border match design detailed in Equation 3. Standard errors are clustered at the occupation level. 95% confidence intervals in red. Spillover coefficients are based on 100% licensure of an occupation's cluster outside their own occupation.

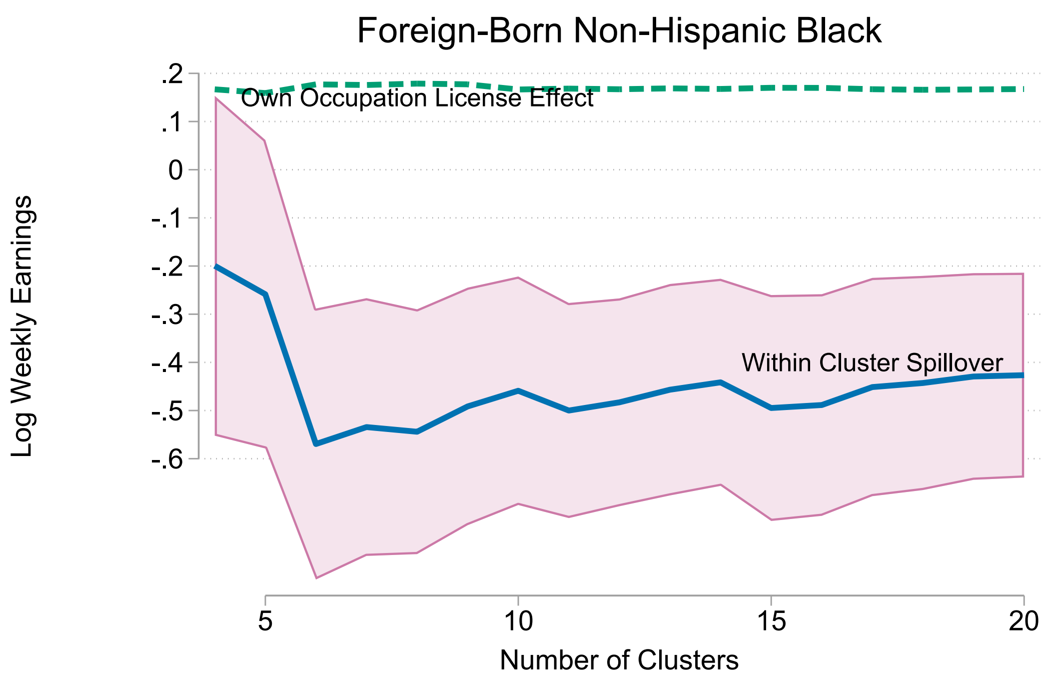
Figure A4: Coefficients of Log Weekly Earnings by Number of Clusters,
Hispanic Workers by Nativity



Source: Author's calculations of ACS, O*NET, and CPS licensing data.
Note: Coefficients are generated from the border match design detailed in Equation 3. Standard errors are clustered at the occupation level. 95% confidence intervals in red. Spillover coefficients are based on 100% licensure of an occupation's cluster outside their own occupation.

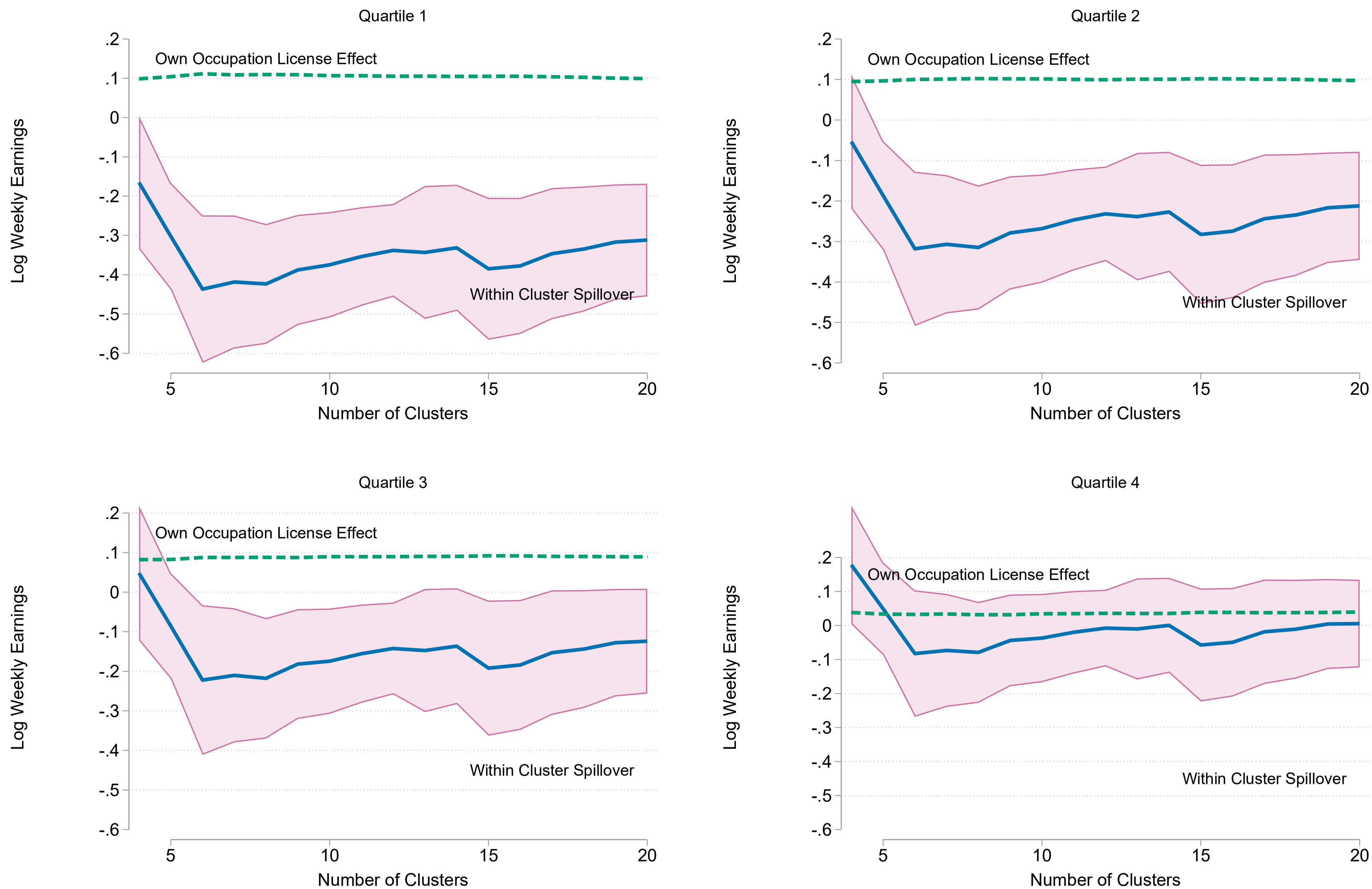
Figure A5: Coefficients of Log Weekly Earnings by Number of Clusters, Non-Hispanic Black Workers by Nativity





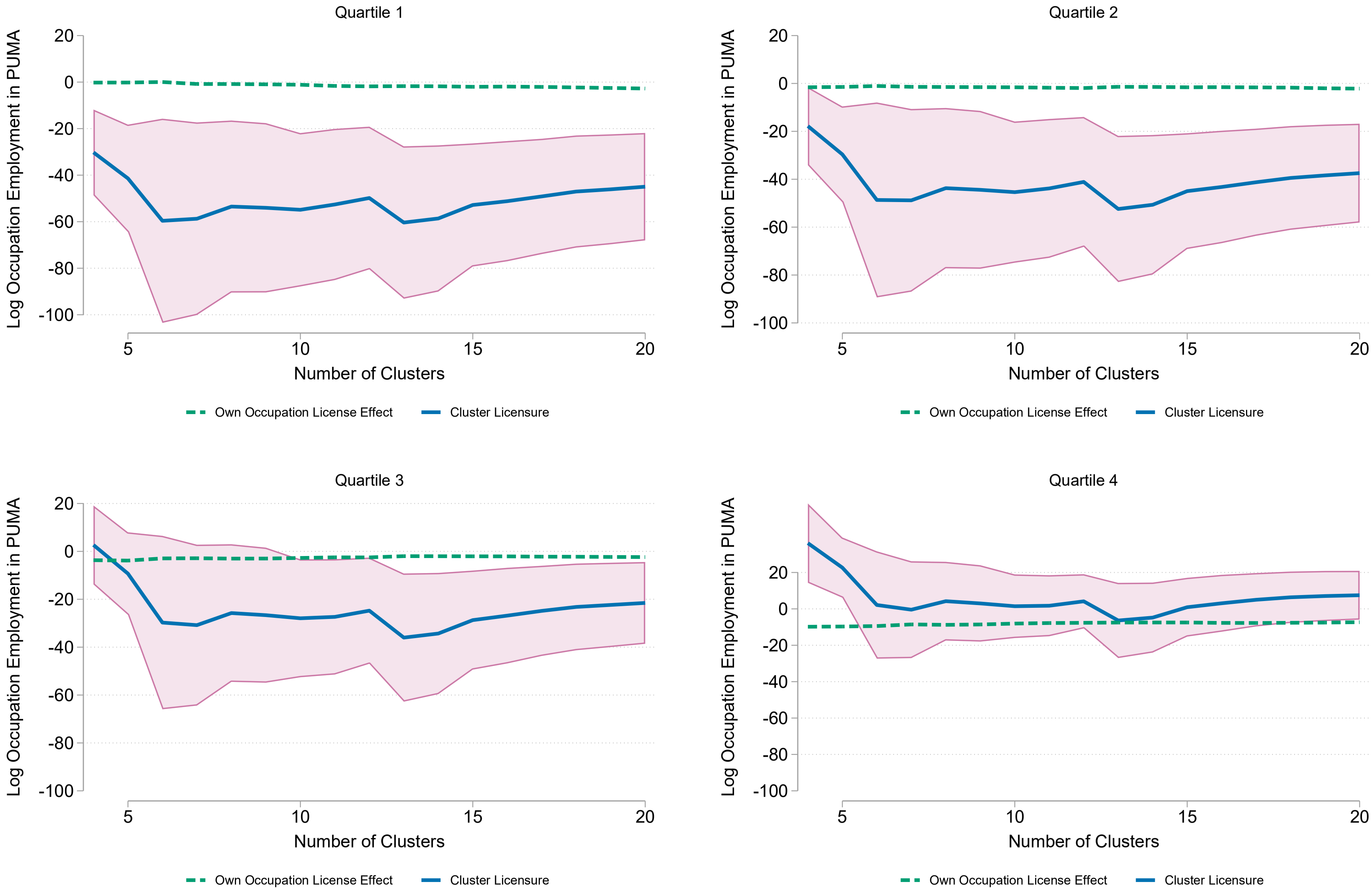
Source: Author's calculations of ACS, O*NET, and CPS licensing data.
Note: Coefficients are generated from the border match design detailed in Equation 3. Standard errors are clustered at the occupation level. 95% confidence intervals in red. Spillover coefficients are based on 100% licensure of an occupation's cluster outside their own occupation.

Figure A6: Coefficients of Log Weekly Earnings by Number of Clusters,
By PUMA Size Quartile



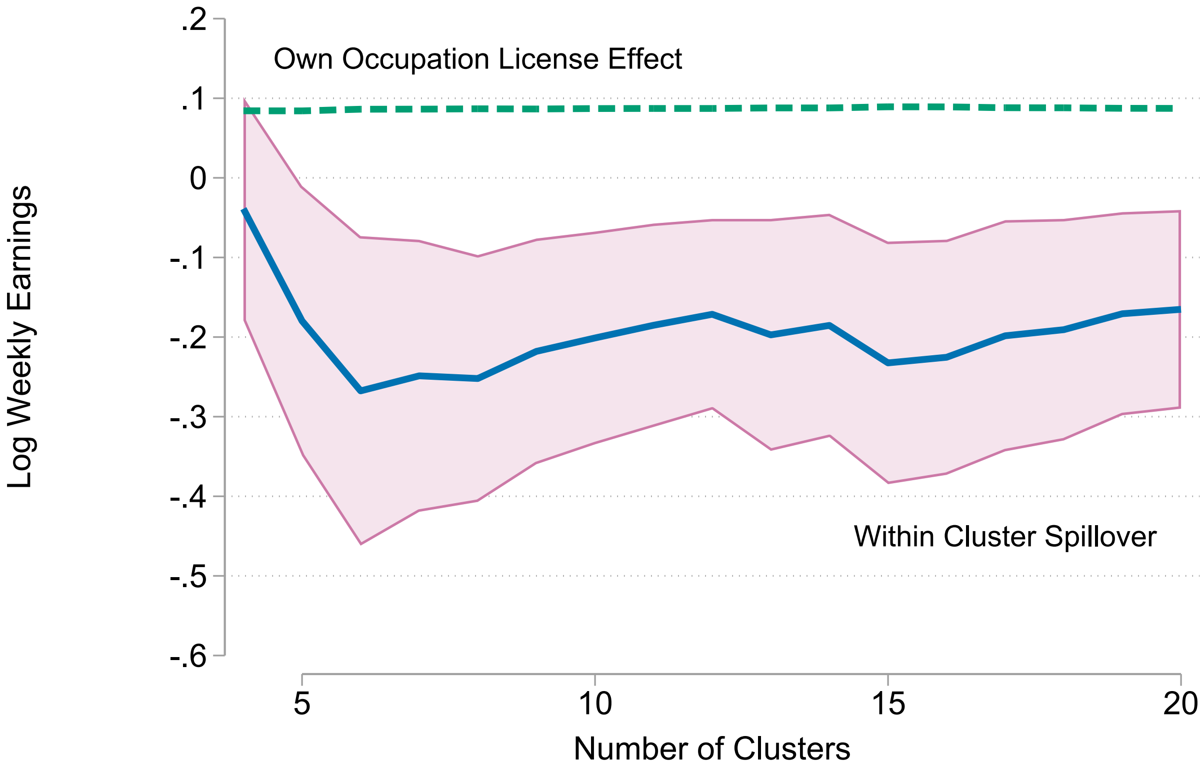
Source: Author's calculations of ACS, O*NET, and CPS licensing data.
Note: Coefficients are generated from the border match design detailed in Equation 3. Standard errors are clustered at the occupation level. 95% confidence intervals in red. Spillover coefficients are based on 100% licensure of an occupation's cluster outside their own occupation.

Figure A7: Coefficients of Employment by Number of Clusters,
By PUMA Size Quartile



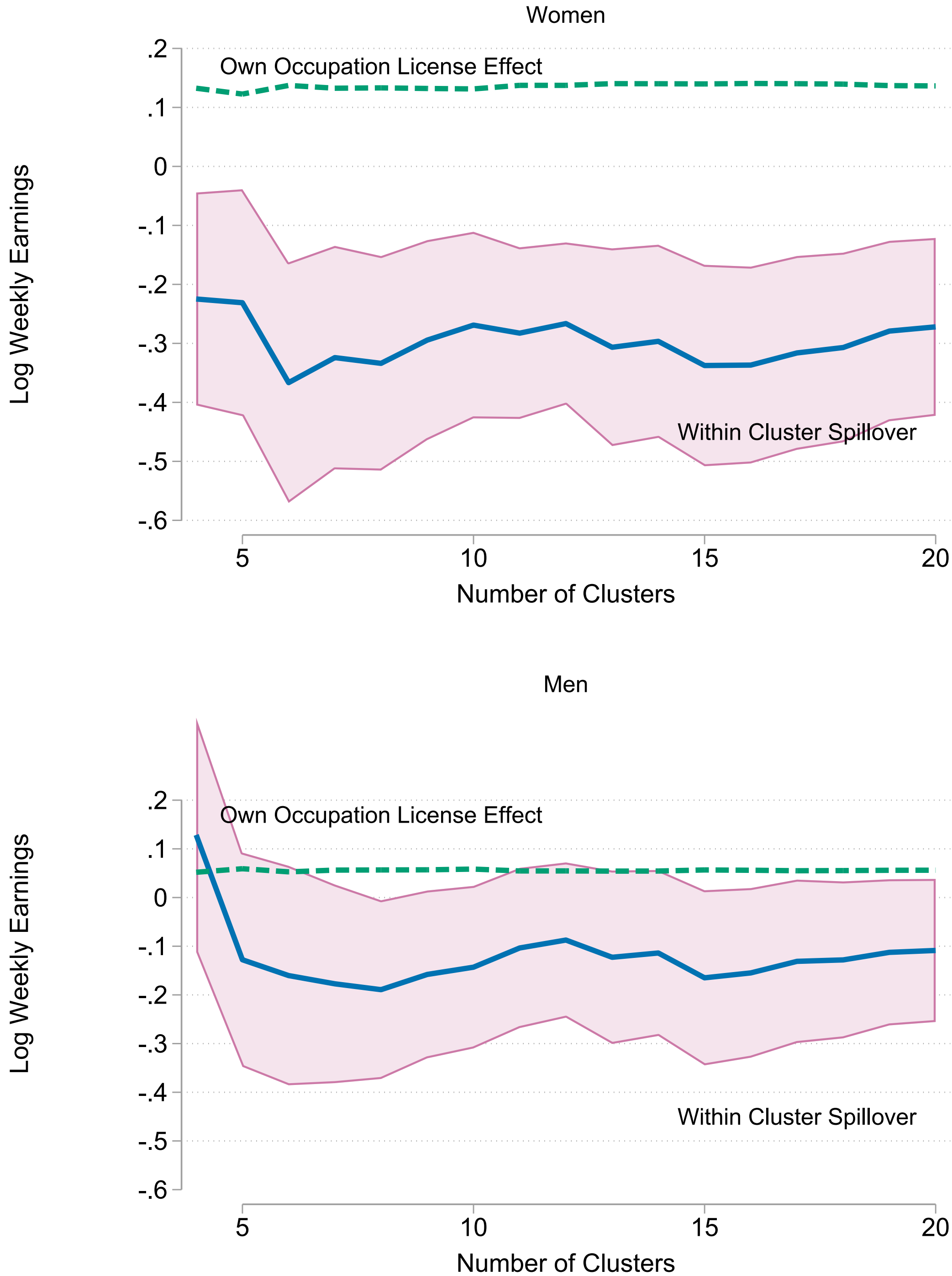
Source: Author's calculations of ACS, O*NET, and CPS licensing data.
Note: Coefficients are generated from the border match design detailed in Equation 3. Standard errors are clustered at the occupation level. 95% confidence intervals in red. Spillover coefficients are based on 100% licensure of an occupation's cluster outside their own occupation.

Figure A8: Coefficients of Log Weekly Earnings by Number of Clusters
All Occupations, Adding PUMA FE



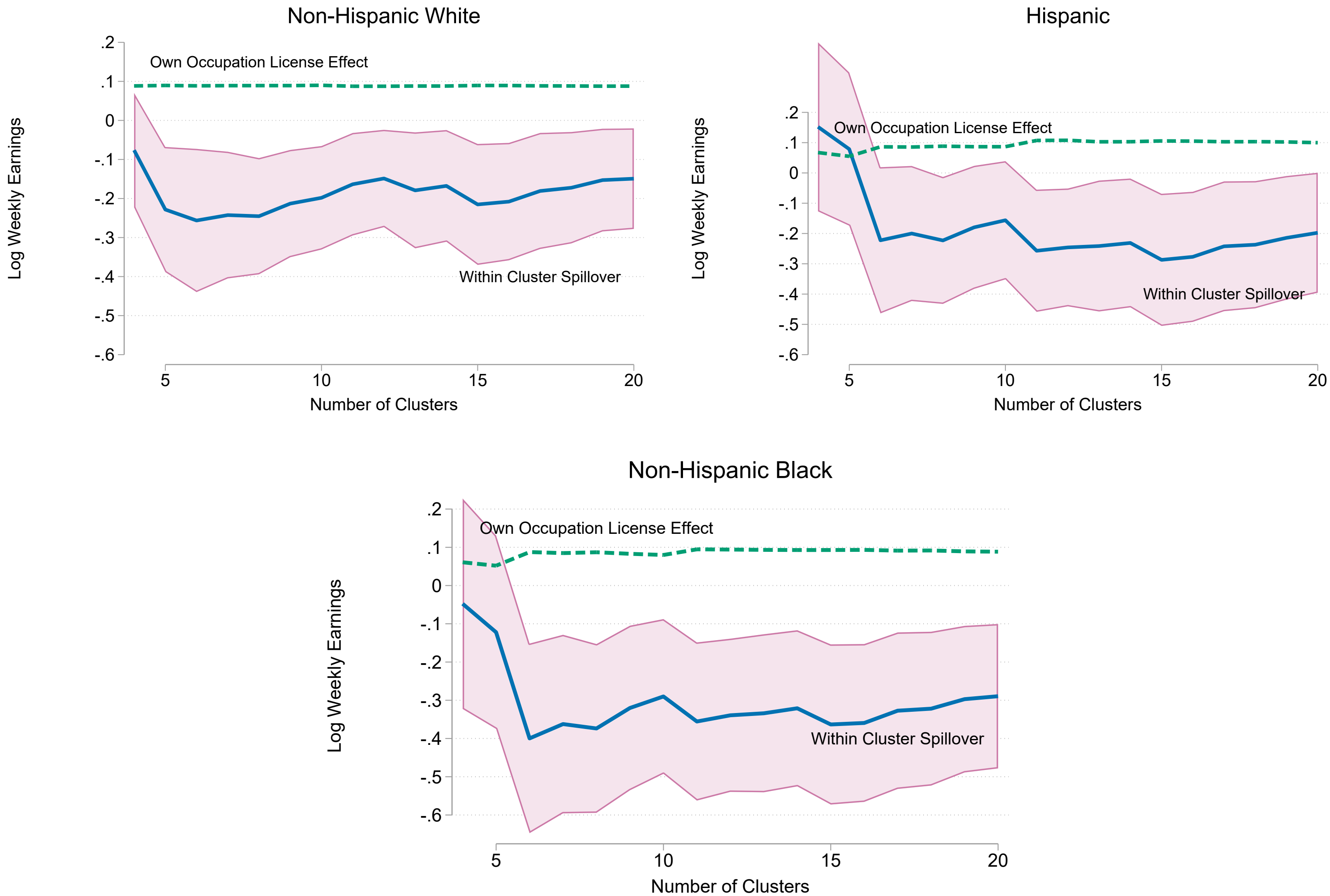
Source: Author's calculations of ACS, O*NET, and CPS licensing data.
Note: Coefficients are generated from the border match design detailed in Equation 3. Standard errors are clustered at the occupation level. 95% confidence intervals in red. Spillover coefficients are based on 100% licensure of an occupation's cluster outside their own occupation.

Figure A9: Coefficients of Log Weekly Earnings by Number of Clusters, by Gender
All Occupations, Adding PUMA FE



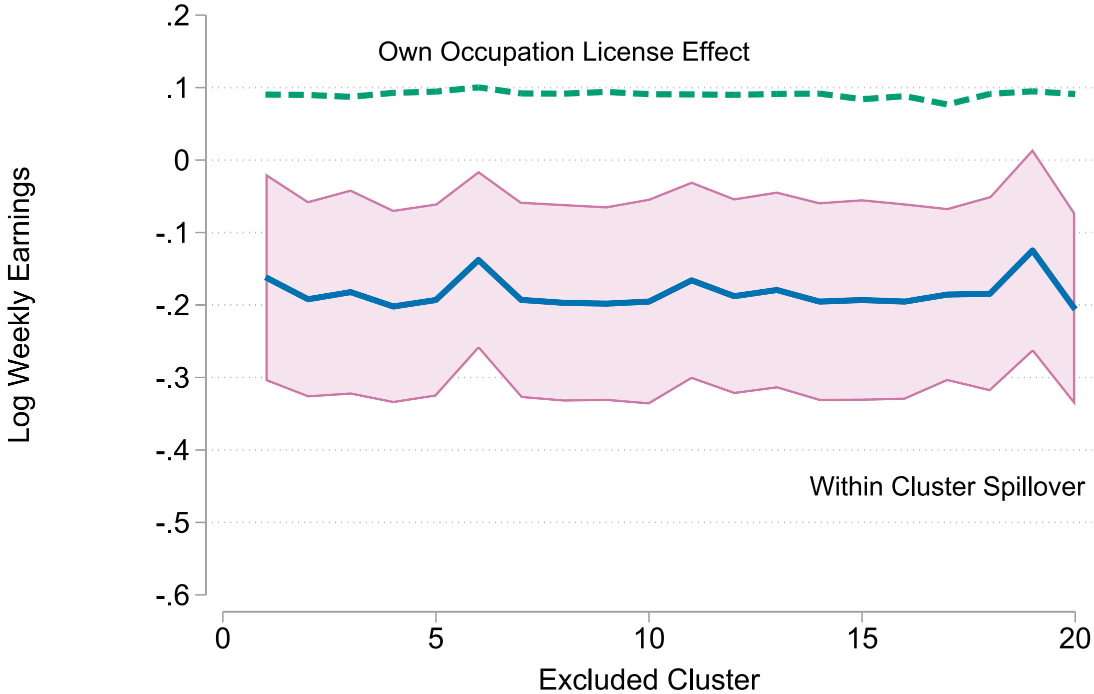
Source: Author's calculations of ACS, O*NET, and CPS licensing data.
Note: Coefficients are generated from the border match design detailed in Equation 3. Standard errors are clustered at the occupation level. 95% confidence intervals in red. Spillover coefficients are based on 100% licensure of an occupation's cluster outside their own occupation.

Figure A10: Coefficients of Log Weekly Earnings by Number of Clusters, by Race/Ethnicity
All Occupations, Adding PUMA FE



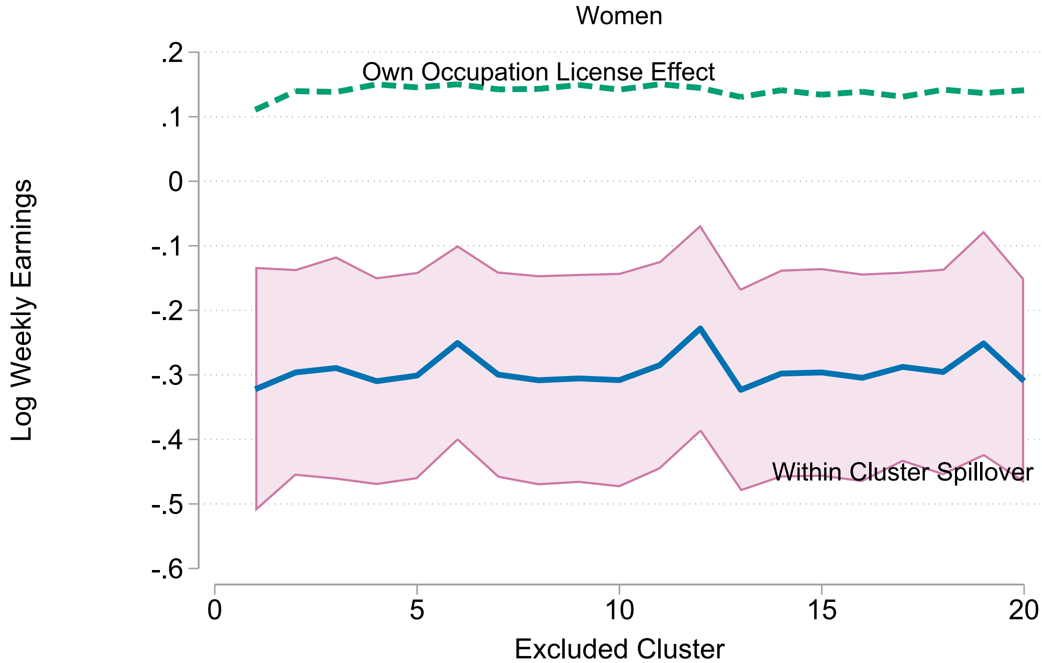
Source: Author's calculations of ACS, O*NET, and CPS licensing data.
Note: Coefficients are generated from the border match design detailed in Equation 3. Standard errors are clustered at the occupation level. 95% confidence intervals in red. Spillover coefficients are based on 100% licensure of an occupation's cluster outside their own occupation.

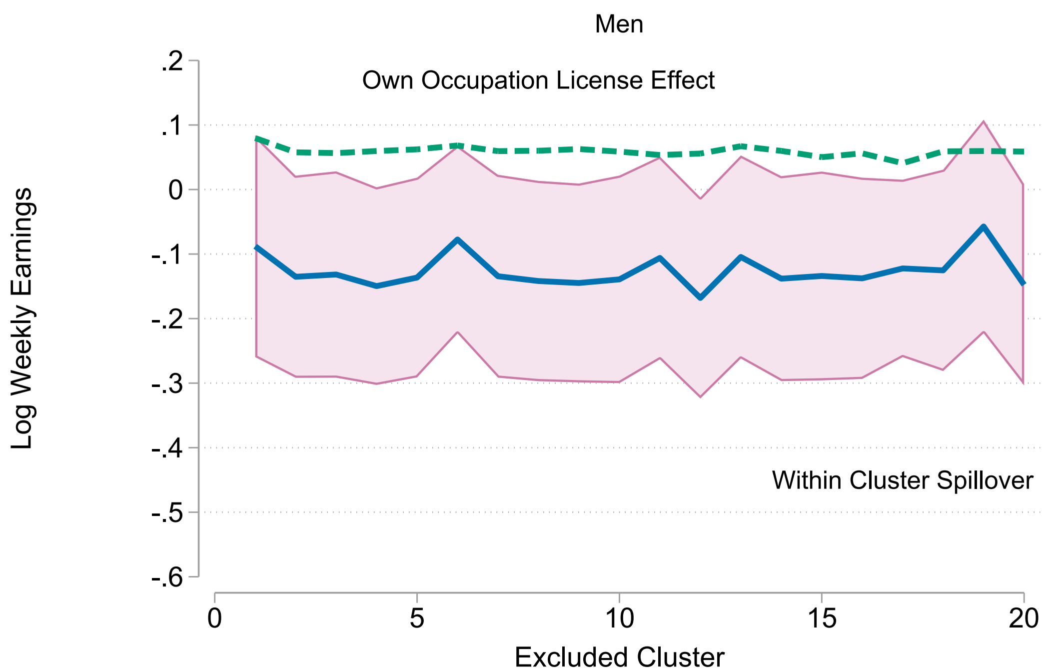
Figure A11: Earnings Effects, Sequentially Removing Clusters
20 Clusters



Source: Author's calculations of ACS, O*NET, and CPS licensing data.
Note: Coefficients are generated from the border match design detailed in Equation 3. Standard errors are clustered at the occupation level. 95% confidence intervals in red. Spillover coefficients are based on 100% licensure of an occupation's cluster outside their own occupation for 20 total defined clusters, eliminating one cluster at a time.

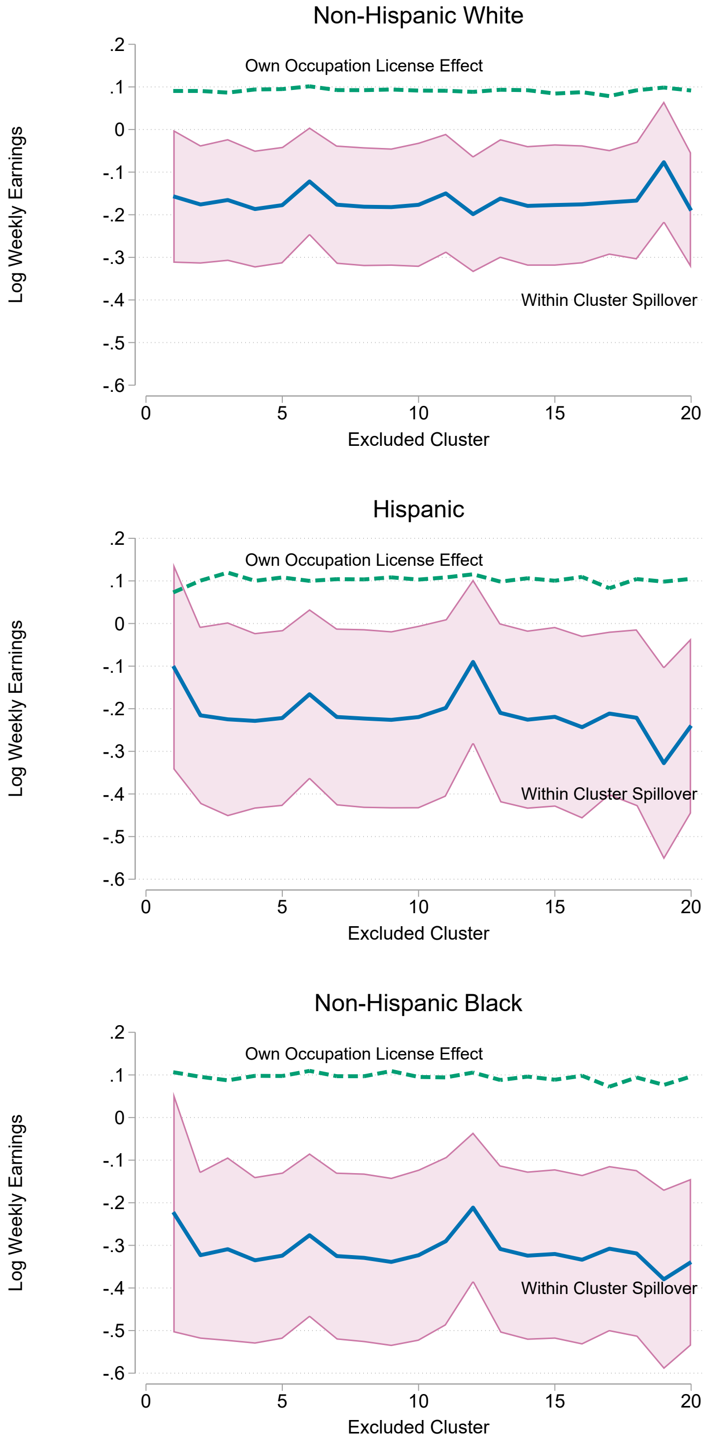
Figure A12: Earnings Effects, Sequentially Removing Clusters
By Gender, 20 Clusters





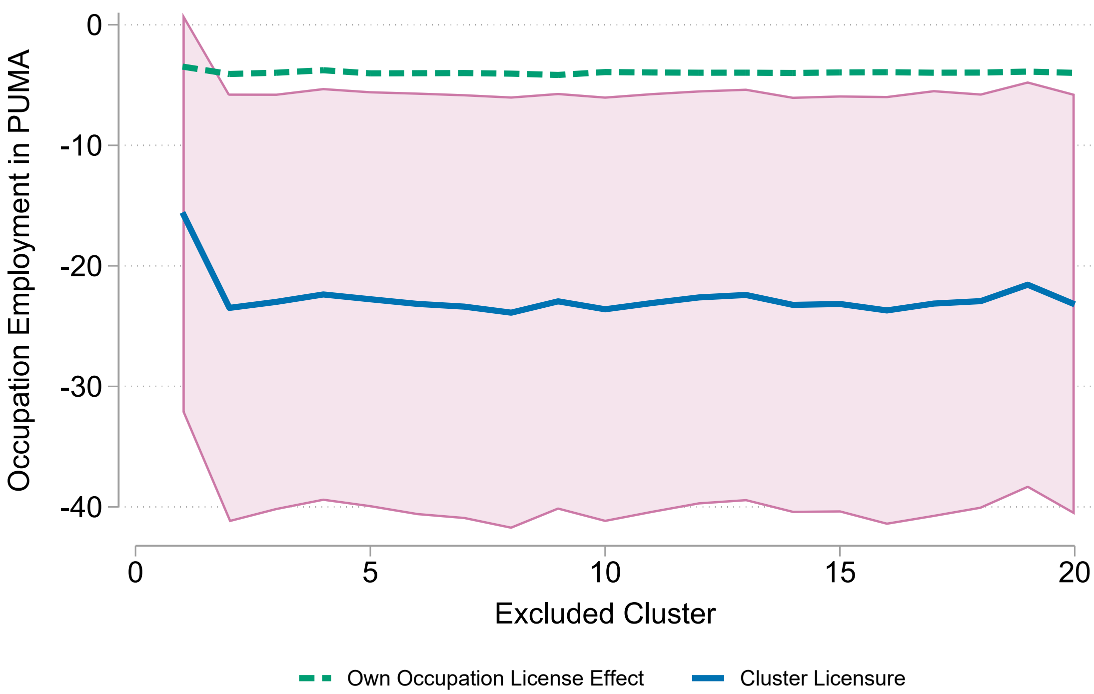
Source: Author's calculations of ACS, O*NET, and CPS licensing data.
Note: Coefficients are generated from the border match design detailed in Equation 3. Standard errors are clustered at the occupation level. 95% confidence intervals in red. Spillover coefficients are based on 100% licensure of an occupation's cluster outside their own occupation for 20 total defined clusters, eliminating one cluster at a time.

Figure A13: Earnings Effects, Sequentially Removing Clusters
By Race/Ethnicity, 20 Clusters



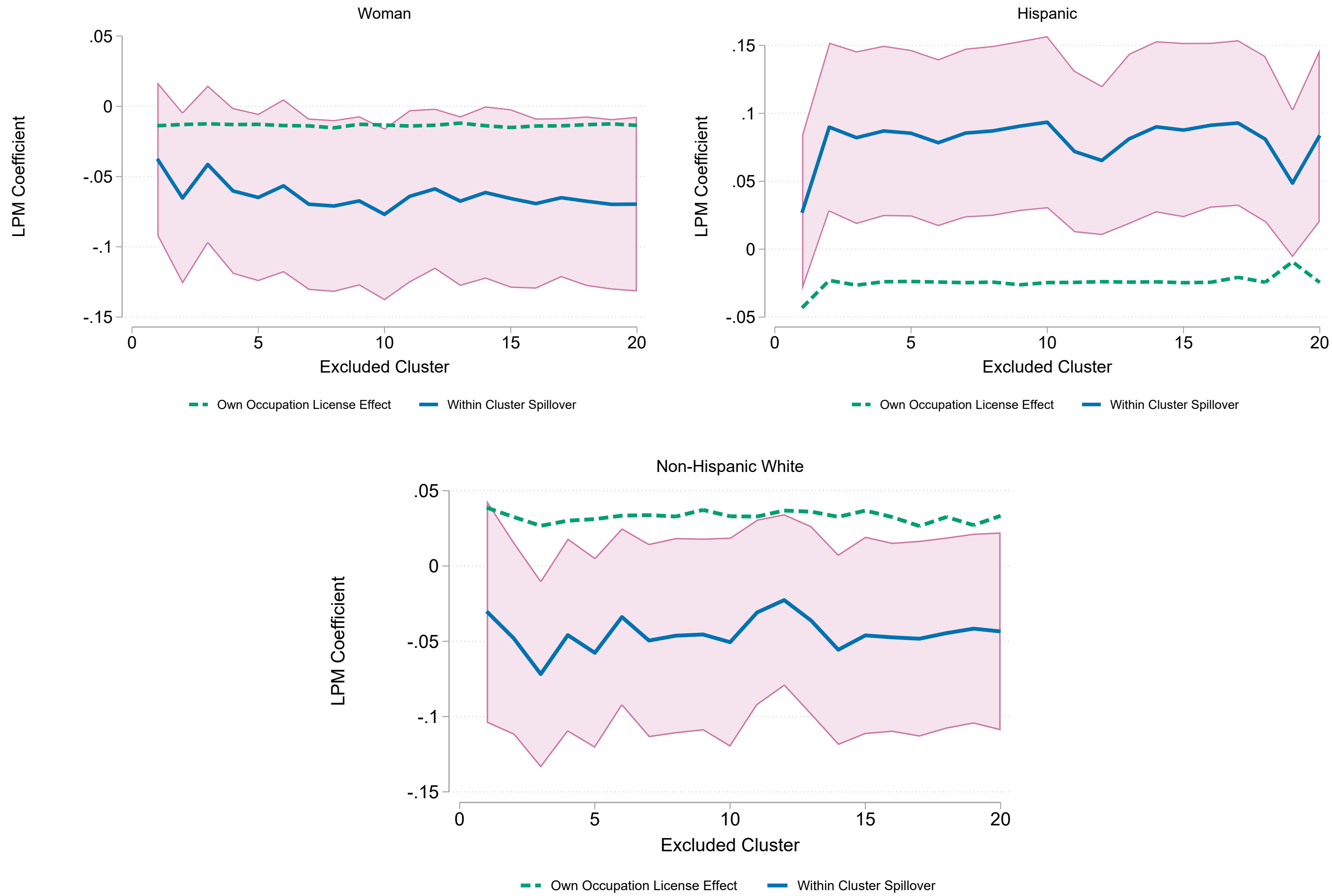
Source: Author's calculations of ACS, O*NET, and CPS licensing data.
Note: Coefficients are generated from the border match design detailed in Equation 3. Standard errors are clustered at the occupation level. 95% confidence intervals in red. Spillover coefficients are based on 100% licensure of an occupation's cluster outside their own occupation for 20 total defined clusters, eliminating one cluster at a time.

Figure A14: Employment Effects, Sequentially Removing Clusters
20 Clusters



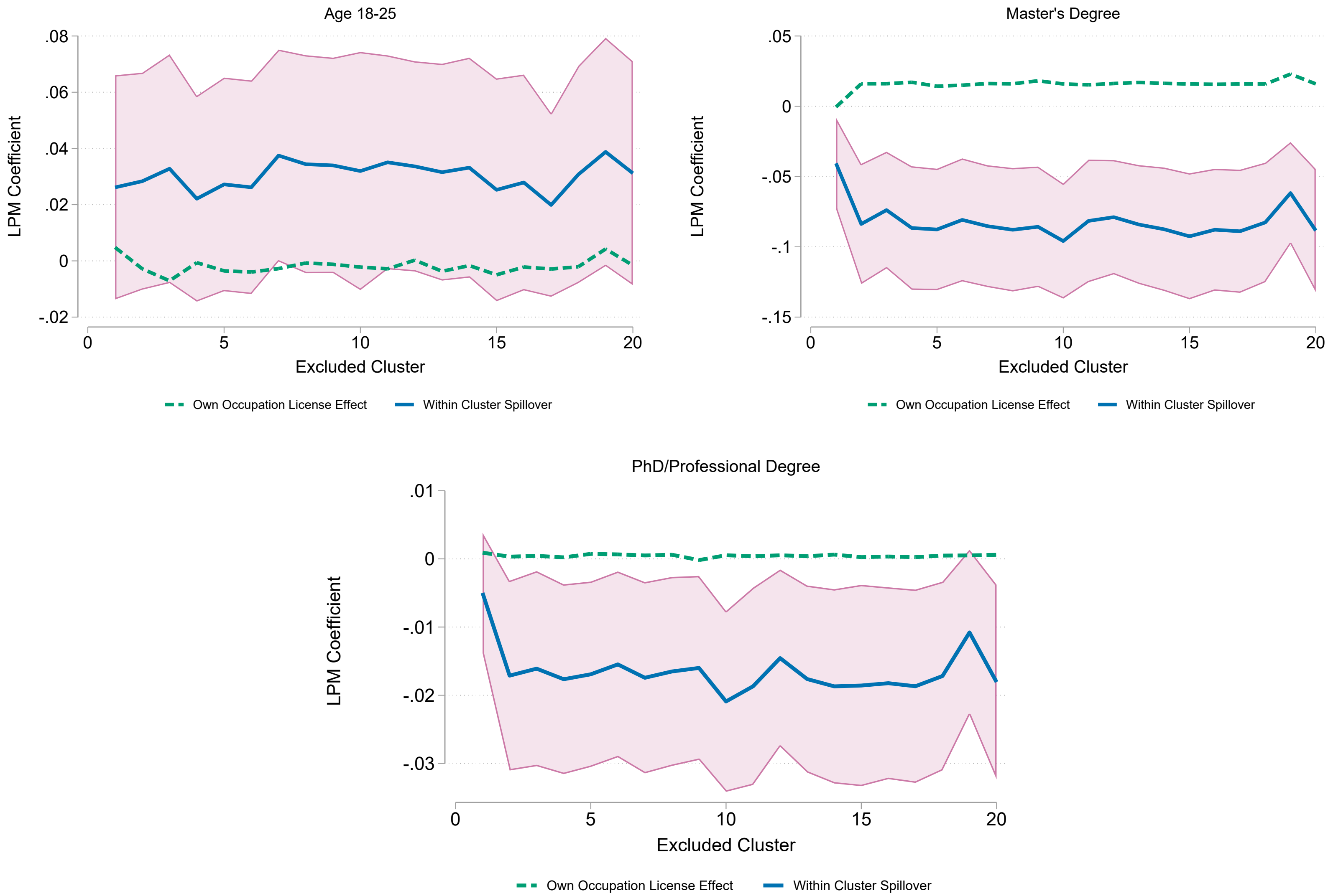
Source: Author's calculations of ACS, O*NET, and CPS licensing data.
Note: Coefficients are generated from the border match design detailed in Equation 3. Standard errors are clustered at the occupation level. 95% confidence intervals in red. Spillover coefficients are based on 100% licensure of an occupation's cluster outside their own occupation for 20 total defined clusters, eliminating one cluster at a time.

Figure A15: Composition Effects, Sequentially Removing Clusters, Sex and Race/Ethnicity
20 Clusters



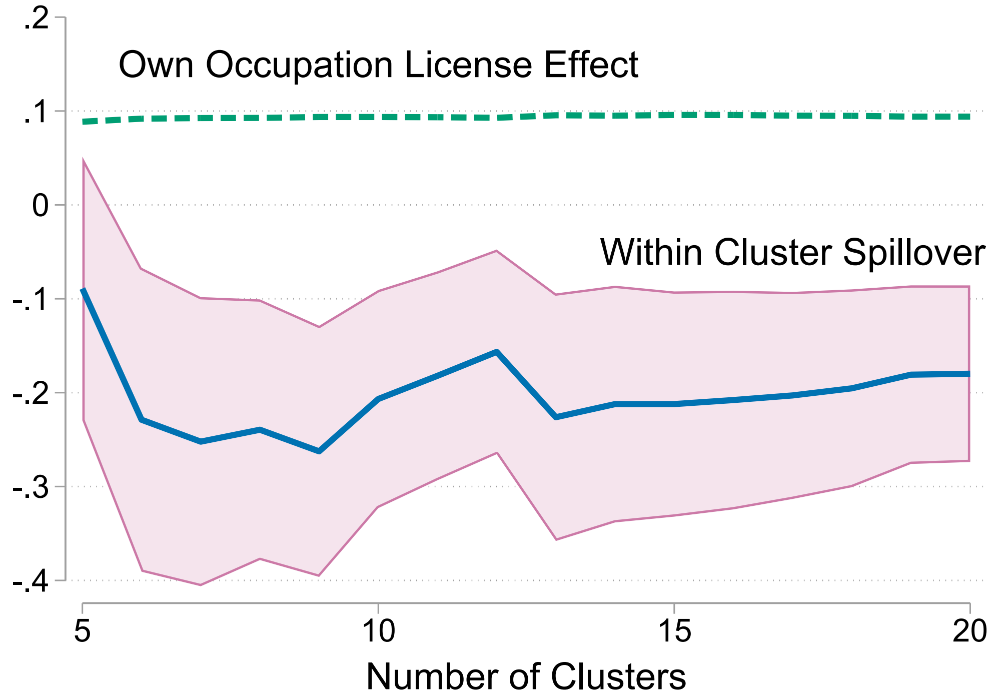
Source: Author's calculations of ACS, O*NET, and CPS licensing data.
Note: Coefficients are generated from the border match design detailed in Equation 3. Standard errors are clustered at the occupation level. 95% confidence intervals in red. Spillover coefficients are based on 100% licensure of an occupation's cluster outside their own occupation for 20 total defined clusters, eliminating one cluster at a time.

Figure A16: Composition Effects, Sequentially Removing Clusters, Age and Education
20 Clusters



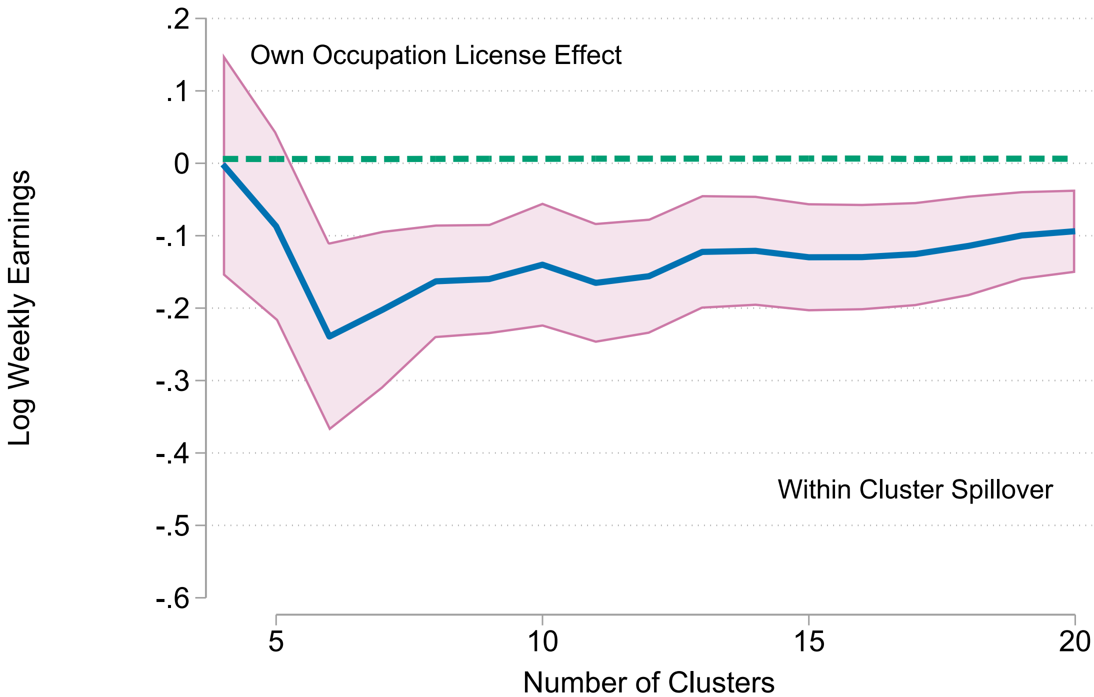
Source: Author's calculations of ACS, O*NET, and CPS licensing data.
Note: Coefficients are generated from the border match design detailed in Equation 3. Standard errors are clustered at the occupation level. 95% confidence intervals in red. Spillover coefficients are based on 100% licensure of an occupation's cluster outside their own occupation for 20 total defined clusters, eliminating one cluster at a time.

Figure A17: Log Wage Effects with CPS 2015-2018
State and Occupation Fixed Effects



Source: Author's calculations of O*NET, and 2015-2018 CPS.
Note: Coefficients are generated from estimates of log hourly wage in the CPS on individual sex, race/ethnicity, age, age squared, and state and occupation fixed effects. Standard errors are clustered at the occupation level. 95% confidence intervals in red. Spillover coefficients are based on 100% licensure of an occupation's cluster outside their own occupation.

Figure A18: Log Earnings Effects using Northwestern Licensing Database



Source: Author's calculations of ACS, O*NET, and Northwestern Licensing Database (NLD) data.
Note: Coefficients are generated from the border match design detailed in Equation 3 using the Northwestern Licensing Database (NLD). Standard errors are clustered at the occupation level. 95% confidence intervals in red. Spillover coefficients are based on 100% licensure of an occupation's cluster outside their own occupation in the NLD.

B Clustering Appendix

There are hundreds of skill, ability, and contextual variables that are a part of the O*NET database. In order to extract meaningful relationships between occupations, it is important to narrow down the set of candidate dimensions over which to cluster them. Failure to reduce the number of variables considered results in the "curse of dimensionality," particularly when attempting a clustering exercise.

One clear option for reducing dimensionality is a principal component analysis (PCA). Below in Figure B1, I present visual comparisons of the dissimilarity matrix using the first six principal components using all of the "skills" in the O*NET database along with the median wage of the occupation. I similarly present the cluster mapping of the first six principal components over all "context" variables in the O*NET database. This dissimilarity value is one minus the Pearson correlation coefficient over all 7 attributes.

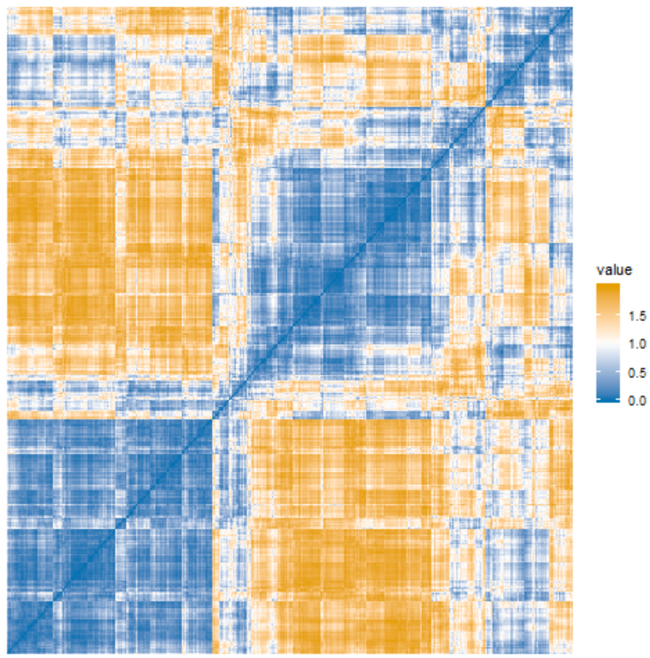
The figure is a colored representation of the dissimilarity matrix. Each occupation is represented on both axes, and the diagonal of the matrix is the distance between each occupation with itself (zero). Darker blue regions represent small differences between occupations along the dimensions considered. In other words, these occupations are highly correlated. Lighter colors and white regions represent occupation pairs that are uncorrelated. The darkest orange areas represent occupations that are highly *negatively* correlated and therefore have the largest distance between them. Importantly, more consistent dark blue and dark orange regions represent more efficient separations or classifications for occupations because the characteristics better capture similarities and differences between occupations.

In turn, clustering over the skills in Acemoglu and Autor (2011) leads to more compact clusters. Table B2 below compares the "height" of the various dendrogram connections between occupations along the three measures considered in Figure B1. The heights represent the correlative distance between the two objects when they merge into a single cluster. Lower values of this height measure indicate tighter or more compact cluster definitions.

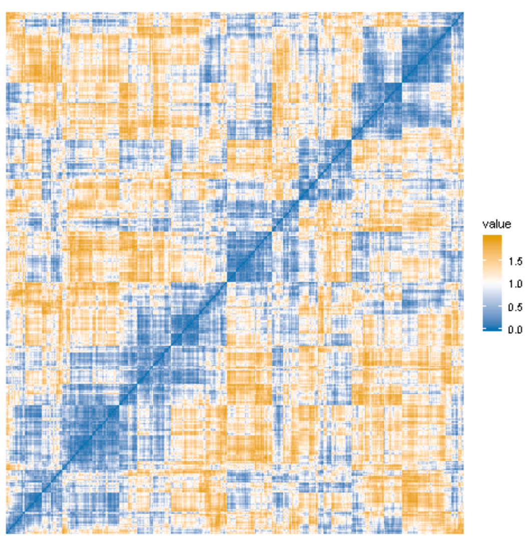
Overall, the measures in Acemoglu and Autor (2011) generate more compact clusters and greater separation between clusters than when clustering over the principal components of the O*NET data. The computer science literature bears this out, stating that in many cases, the principal components of the data, while capturing the greatest variation across the attributes, do not capture the *cluster* structure of the data as well as using a subset of the variables (Yeung and Ruzzo, 2001). As a result, what one would consider the "data-driven" approach to choosing attributes over which to cluster yields worse cluster matching. The alternative is either an ad hoc or a theory-driven choice of clustering attributes. The theoretical and empirical literature on worker skills supports the framework in my analysis, and the empirical exercise I present justifies using this approach over the principal-component approach.

Figure B1: Correlative Distance Values Between Occupations

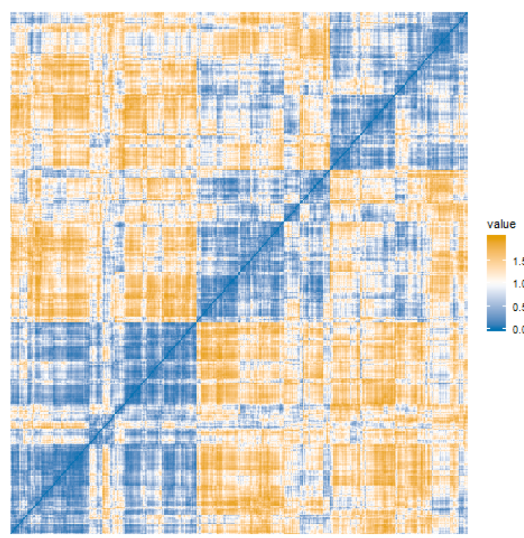
Panel A: Skills in Acemoglu and Autor (2011)



Panel B: PCA on O*NET "Skills"



Panel C: PCA on O*NET "Context"



Source: Author's calculations of O*NET data.

Notes: Each panel is a matrix of the correlative distance in the seven attributes between each occupation pair, which is one minus the Pearson correlation coefficient. Darker blue represents the smallest differences between occupations along the dimensions considered, while the darkest orange colors represent the largest possible differences between the occupations. More consistent dark blue and dark orange regions represent better separations or classifications for occupations.

Table B1: Top 5 Focal Occupations by Cluster

Occupation	Cluster	Freq	Rank
Managers, Nec (Including Postmasters)	1	161944	1
Elementary And Middle School Teachers	1	161405	2
Accountants And Auditors	1	75768	3
Postsecondary Teachers	1	59665	4
Computer Scientists And Systems Analysts/Network Systems Analysts/Web Developers	1	59412	5
Farmers, Ranchers, And Other Agricultural Managers	2	15456	1
Heating, Air Conditioning, And Refrigeration Mechanics And Installers	2	13725	2
Bus And Truck Mechanics And Diesel Engine Specialists	2	12739	3
Electronic Home Entertainment Equipment Installers And Repairers	2	1356	4
Home Appliance Repairers	2	1092	5
Chefs And Cooks	3	90676	1
Nursing, Psychiatric, And Home Health Aides	3	71725	2
Waiters And Waitresses	3	70596	3
Personal Care Aides	3	44406	4
Food Service And Lodging Managers	3	36221	5
Secretaries And Administrative Assistants	4	136243	1
Customer Service Representatives	4	98746	2
Receptionists And Information Clerks	4	41797	3
Medical Assistants And Other Healthcare Support Occupations, Nec	4	33470	4
Security Guards And Gaming Surveillance Officers	4	33186	5
Software Developers, Applications And Systems Software	5	47609	1
Computer Programmers	5	16904	2
Engineering Technicians, Except Drafters	5	16298	3
Paralegals And Legal Assistants	5	15156	4
Claims Adjusters, Appraisers, Examiners, And Investigators	5	11561	5
Police Officers And Detectives	6	35700	1
Editors, News Analysts, Reporters, And Correspondents	6	9325	2
Biological Scientists	6	3498	3
Construction And Building Inspectors	6	3318	4
Private Detectives And Investigators	6	3071	5
Radio And Telecommunications Equipment Installers And Repairers	7	6138	1
Surveying And Mapping Technicians	7	2584	2
Transportation Inspectors	7	1690	3
Electrical And Electronics Repairers, Transportation Equipment, And Industrial And Utility	7	700	4
Geological And Petroleum Technicians, And Nuclear Technicians	7	674	5
Data Entry Keyers	8	13733	1
Production, Planning, And Expediting Clerks	8	13599	2
Dental Assistants	8	11273	3
Agricultural And Food Science Technicians	8	1763	4
Prepress Technicians And Workers	8	992	5

Office Clerks, General	9	51245	1
Bookkeeping, Accounting, And Auditing Clerks	9	47800	2
Billing And Posting Clerks	9	19213	3
Diagnostic Related Technologists And Technicians	9	15015	4
Insurance Claims And Policy Processing Clerks	9	14547	5
Life, Physical, And Social Science Technicians, Nec	10	8709	1
Animal Control	10	302	2
Sales Representatives, Services, All Other	11	23563	1
Actors, Producers, And Directors	11	6821	2
Advertising Sales Agents	11	6014	3
Community And Social Service Specialists, Nec	11	3616	4
Eligibility Interviewers, Government Programs	11	3191	5
Cashiers	12	106546	1
Stock Clerks And Order Fillers	12	59355	2
Maids And Housekeeping Cleaners	12	38977	3
Food Preparation Workers	12	31460	4
Shipping, Receiving, And Traffic Clerks	12	23018	5
First-Line Supervisors Of Sales Workers	13	156541	1
Retail Salespersons	13	111932	2
Childcare Workers	13	31616	3
Recreation And Fitness Workers	13	14611	4
Athletes, Coaches, Umpires, And Related Workers	13	9313	5
First-Line Supervisors Of Construction Trades And Extraction Workers	14	30855	1
First-Line Supervisors Of Mechanics, Installers, And Repairers	14	12044	2
Photographers	14	4030	3
First-Line Supervisors Of Fire Fighting And Prevention Workers	14	2197	4
Electricians	15	30869	1
Aircraft Mechanics And Service Technicians	15	7138	2
Tool And Die Makers	15	2481	3
Precision Instrument And Equipment Repairers	15	2166	4
Security And Fire Alarm Systems Installers	15	2037	5
Painters, Construction And Maintenance	16	14140	1
Firefighters	16	12405	2
Dishwashers	16	9838	3
Roofers	16	5876	4
Electrical Power-Line Installers And Repairers	16	5415	5
Agricultural Workers, Nec	17	34934	1
Bus And Ambulance Drivers And Attendants	17	20930	2
Crossing Guards	17	1671	3
Motor Vehicle Operators, All Other	17	1133	4
First-Line Supervisors Of Production And Operating Workers	18	39633	1
First-Line Supervisors Of Housekeeping And Janitorial Workers	18	7236	2
Counter Attendant, Cafeteria, Food Concession, And Coffee Shop	18	5017	3
First-Line Supervisors Of Landscaping, Lawn Service, And Groundskeeping Workers	18	4659	4

First-Line Supervisors Of Farming, Fishing, And Forestry Workers	18	2630	5
Janitors And Building Cleaners	19	87855	1
Laborers And Freight, Stock, And Material Movers, Hand	19	84622	2
Construction Laborers	19	53641	3
Other Production Workers Including Semiconductor Processors And Cooling And Freezing Equipment Operators	19	50467	4
Assemblers And Fabricators, Nec	19	39839	5
Stationary Engineers And Boiler Operators	20	3551	1
Locksmiths And Safe Repairers	20	761	2
Electronic Equipment Installers And Repairers, Motor Vehicles	20	302	3

Source: Author's calculations of ACS and O*NET data.

Notes: Clusters are based on description in Section 4.1. ACS samples are from 2014-2017.

Table B2: Comparison of Tree Height at Cutpoints

Distance at Cluster Merge	Skills in AA (2011)	PCA Skills	PCA Context
Mean	0.1137	0.1423	0.1556
Min	0.0008	0.0041	0.0040
P25	0.0270	0.0459	0.0540
P50	0.0594	0.0886	0.1078
P75	0.1360	0.1662	0.1950
Max	1.3658	1.1667	1.2663

Source: Autor's calculations of version 22.0 of the O*NET database (2017) and Acemoglu and Autor (2011).

Notes: Summary statistics come from the shape of the dendrogram (tree) from the Hierarchical Agglomerative Clustering procedure. The "height" of the connection between occupations and clusters is the correlative distance between them when the two objects merge into a single cluster. Lower values of the height represent tighter or more compact cluster definitions and closer relationships between objects.

C Model of Skill Transferability

The model in Shaw (1987) makes clear predictions about how skill transferability between occupations determines switching and investments into occupation-specific human capital. This model suggests conditions under which an individual in an occupation will change their occupation.

While my setting does not consider job changes per se, I conceptualize occupational choice as selecting an occupation that best matches with latent skills, either endowed or acquired through investment. Rather than past investment in the occupation's skillset, initial conditions are dependent on endowed skills when entering the labor market, either through family or public investments or innate ability. These can include any skills which make the individual suited for a set of occupations, like sociability, physical strength, cognitive ability, or leadership skills. The initial "occupation" represents the occupation for which the combination of an individual's endowed skills is best suited at baseline, or whose I_0 is largest.

Following Shaw (1987), I define the occupational human capital stock for a person in occupation j at time t (I_t^j) as:

$$I_t^j \equiv K_t^j + \gamma^{ij} K_{t_j-1}^i + ... + \gamma^{gj} K_{t_i-1}^g + I_0^j + \sum_{e=i,h,g} \gamma^{je} I_0^e \tag{4}$$

where an individual's human capital in occupation j depends on time spent in the occupation since they entered the occupation (t_j) and on the human capital investments in all other occupations $i, h, ...g$ which were entered into at time $t_{i,h,...g}$. The final term is the sum of all initial endowments in skills related to each occupation. The endowment term gives a baseline for occupation choice structure. Essentially, all workers, as they enter the labor market, have a "default" occupation into which they would sort given their endowed comparative advantage. Further investment choices are afterward driven by comparison to this baseline. In short, this full equation represents the total investments through the current period in human capital for occupation j, including transferable skills in i through g. Importantly, γ^{ij} is the share of skills in occupation pair i, j that is transferable between the two occupations.

Each K^j is defined as the sum of all the earnings capacity invested in occupation j in each year because time spent investing in human capital for an occupation is time not spent on production. Investment intensity, or the share of productive capacity used in developing human capital, is k_t^j, so realized earnings (Y) in the current period are some share of earnings capacity (E), where $Y_t = E_t(1 - k_t^j) + I_0$.

Simplifying a Mincer equation (Mincer, 1974) of earnings in which individual costs of investment C^j directly translate into earnings through K^j in the period after investment, income in the current period t in occupation j can be expressed:

$$Y_t^j = E^s + r^j(C_{t-1}^j + \gamma^{ij} C_{t_j-1}^i) - c_t^j + \gamma^{ij} I_0^i + I_0^j \tag{5}$$

Here, E^s is earnings capacity or general human capital given formal schooling, and r^j is a common rate of return to investments in j. The C terms are at the individual level and represent the current stock of accumulated earnings capacity in j until period $t-1$ as well as the earnings capacity due to skill transferability from occupation i accumulated before the change to occupation j. The term c_t^j captures current investment in j. In words, earnings capacity today is a function of schooling, returns to all accumulated investments in j, the share of investments in i that are transferable to j, endowed capacity in j, and the share of endowed capacity in i that is transferable to j net of current investments in j.

In present value terms, given discount rate r, an individual will switch occupations from i to j when:

$$\{\gamma^{ij} r^i C^i_{t-1} - r^j C^j_{t-1} + (\gamma^{ij} I^i_0 - I^j_0)\} \sum_{g=t}^{T} (1/(1+r)^g)) < 0 \tag{6}$$

and

$$\sum_{g=t}^{T} \sum_{h=t}^{g-1} \{(r^j c^j_h - c^j_g) - (r^i c^i_h - c^i_g)\}(1/(1+r)^g) \lesseqgtr 0 \tag{7}$$

Equation 6 represents the loss of returns to past investments and endowments in occupation i. Because $\gamma^{ij} < 1$, there is a loss associated with switching occupations in which past investments into j no longer reap rewards except through skill transferability. The present value of gains to investment in j must be large enough to overcome the difference between 1 and the value of γ^{ij}.

Equation 7 is the difference in the value of future investment in occupation j vs occupation i. When the value of future investments in j is larger, the worker will choose to absorb the costs of entering j rather than i. There are two key predictions of this model: 1) the greater the skill transferability, γ^{ij}, the more probable a move between the two will be; 2) lower opportunities for investment in i will increase the value of moving to j.

An occupational license in i may affect the balance of these inequalities. A license that categorically blocks entry for some demographic groups such as non-residents, non-English speakers, or those who have been incarcerated sharply reduces opportunities for investment in i and therefore increases the value of moving to j. The same holds if the costs of investment c^i rise with additional education requirements, exams, or fees without offsetting returns through C. Alternatively, an occupational license may directly influence occupational skill substitutability by introducing requirements for an occupation that may be unrelated to the performance of the job.[24]

If the transferability of skills is highest in the i, j combination over some set of other occupations, say, i, h, the first order choice is whether or not to move between i and j. If j is *also* licensed with large investment costs, the worker may move to the next comparison, h. In terms of my setup, this implies that occupational licenses will push individuals out of licensed occupations in their skill cluster and into the most related occupations in the same cluster, increasing labor supply in a competitive labor market, and reducing wages. If, however, licensing is widespread enough and adjustment costs are large, individuals may exit the cluster altogether.

[24] For example, Florida bill 851 required massage therapists, acupuncturists, dentists, pharmacists, and other health care professionals to be trained in spotting and reporting human trafficking violations and post signs regarding human trafficking in conspicuous places in their establishments as a condition of licensure. https://www.flsenate.gov/Committees/BillSummaries/2019/html/2089 (Accessed April 30, 2020).