# Occupational Licensing, Skills, and Labor Market Spillovers

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**Abstract**

Research on occupational licensing suggests that licenses reduce labor supply and generate a wage premium. Rather than effects on one's own occupation, I test for the presence of wage spillovers onto other occupations with similar latent skills. Using data from O*NET, I cluster occupations together using Hierarchical Agglomerative Clustering. Leveraging cross-state variation in individual licensing status from the CPS, and using a border discontinuity design on individual ACS microdata, I estimate the labor market spillovers of licenses onto other occupations. I find that a 10 percentage point increase in licensure rates in related occupations reduces individual earnings in one's own occupation by approximately 2-2.5%. These effects are particularly strong for women, Non-Hispanic black, and foreign-born Hispanic workers. Licensing spillovers shift the composition of workers in related occupations. Contrary to a standard labor supply prediction, overall employment falls in related occupations. Falling earnings combined with falling employment are more in line with the predictions of a monopsony model where licensing reduces the feasibility of outside options and increases search costs.

**JEL Codes:** J21, J24, J42, L51

# 1 Introduction

Occupational licensing can be considered state-sanctioned permission to work in a particular occupation. Across the United States and Europe, licensing as a feature of the labor market has grown substantially over the last fifty years to affect over 20% of workers across both major economies (Cunningham, 2019; Koumenta et al., 2014). As licensing grows, it becomes more and more important to understand how these regulations affect the well-being of workers in the labor market.

The current literature suggests that occupational licensing regulations, particularly marginal licenses which differ across states, reduce overall labor supply into licensed occupations (Blair and Chung, 2019; Kleiner and Soltas, 2019), shift the composition of labor supply (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 (Johnson and Kleiner, 2017; Kugler and Sauer, 2005). There is also some evidence of wage spillovers for occupations that perform similar functions in the same industry, namely health care (Cai and Kleiner, 2016; Kleiner and Park, 2010; Kleiner et al., 2016). Each of these findings suggest substantial costs to workers and society in pursuit of the health and safety protections used to justify these regulations.

As an important extension of this literature, I ask the following question: if occupational licenses increase barriers to entry, reduce labor supply into an occupation, and reduce interstate migration, what are the effects of that rigidity on the structure of earnings in other occupations? My simple hypothesis is that widespread licensing may have spillover effects on occupations that use similar latent skills. A downward shift in labor supply into licensed occupations as well as the barrier to entry itself can create wage pressure through labor supply reallocation to unlicensed occupations or an increase in monopsony power as outside options become costlier to enter and search costs increase. Licensing may also change the composition of the occupation because of differential adjustment costs across demographic groups.

In this paper, I test for the presence of spillovers in three steps. First, I group occupations together based on their skill content. I use data on the various skill components in the Occupational Information Network (O*NET) database and non-parametric clustering techniques to group together occupations which require similar levels of key skills and which receive 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, as well as the nationwide occupation median wage.[1]

Second, using individual licensing data from the Current Population Survey, I leverage cross-state variation in individual licensing status within the state-cluster cell outside one's own occupation (which I call the "focal occupation") as a proxy for the regulatory environment (Kleiner and Soltas, 2019). My main empirical approach uses microdata from the American Community Survey in a border discontinuity design to compare the earnings of workers in the same occupation on either side of a state border in which the labor markets are likely to be very similar with the exception of the licensing environment. Because the licensing environment is defined at the state level, this is assumed to be exogenous to other local labor market factors. I compare the the earnings of observably similar workers in the same occupation across a state border who differ in the share of the skill cluster *outside* their own occupation that is licensed. I also estimate the effects on the composition of workers in the occupation.

Third, I estimate the effects of clusterwide licensure on employment in each focal occu-

[1] I argue this is preferable to using empirically observed job transitions in publicly available datasets to cluster occupations because job-to-job transitions are endogenously determined by both wage-related and non-work reasons for leaving a particular occupation or job, and job-to-job transitions may be transitory in nature. For example, many people employed in the arts work during off-season periods or between years at restaurants or other service jobs for reasons unrelated to wages and skill similarity, but for reasons related to hours flexibility and the temporary nature of the work. In addition, publicly available datasets like the CPS do not measure more long-term job changes, but capture short term job shifts (Kambourov and Manovskii, 2008).

pation. 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 remaining occupations? The direction of this effect informs the underlying mechanism behind any spillovers.

Consistent with the prior literature, I find an average earnings premium of approximately 10 percent in occupations required to have a license in their state relative to the same occupation in non-licensed jurisdictions 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 2-2.5% *lower* within their own occupation. In other words, if every other occupation in one's skill cluster became fully licensed, wages in one's own occupation would decline by approximately 20%. These effects are particularly pronounced for women, non-Hispanic black, and foreign-born Hispanic workers.

These earnings spillovers can come through two competing mechanisms: 1) a labor supply effect where workers in the skill cluster sort into the focal occupation or remaining unlicensed occupations; or 2) a reduction in the set of outside options available to a worker in the focal occupation, which leads to greater labor market frictions that may exacerbate the negative wage effects of monopsony power in a local labor market (Kleiner and Park, 2010).[2]

A pure labor supply effect would be consistent with within-cluster shifts to unlicensed occupations. Under sorting pressures, those less able to absorb licensing costs would be more likely to end up in unlicensed occupations in the cluster, which may increase total employment in the focal occupation. For complementary skills, this is preferable for licensed occupations (Persico, 2015). On the other hand, a fall in overall labor supply to the focal occupation coupled with wage declines is consistent with a monopsony model of the labor market, as monopsonistic firms higher fewer workers and pay lower wages (Ashenfelter et al., 2010).

I find little evidence of direct labor supply spillovers. Even though I find that a greater

[2]The composition of workers in the occupation may also shift, but these changes are predicted by both a labor supply effect and a monopsony effect.

share of skill cluster employment feeds into the focal occupation, as cluster-wide licensing grows, absolute entry into the cluster falls, leading to a decline in the absolute number of workers in the focal occupation. This finding of overall falling equilibrium employment and lower earnings in the focal occupation is not consistent with an upward shift in labor supply driving down wages. Instead, these findings are consistent with monopsony search models.

In terms of composition changes, I find that if a cluster outside the focal occupation becomes fully licensed, the share of workers in the focal occupation who are women or have a Master's degree or PhD falls. I also find that the share of workers in the focal occupation that are Hispanic or foreign-born rises sharply by over 8 percentage points. Along other dimensions, there are minimal shifts in composition.

My findings are robust to the inclusion of local area (PUMA) fixed effects. This specification limits identifying variation to only areas who 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. [3]

This paper contributes to the growing empirical literature on the effects of occupational licensing on the labor market, particularly in the context of labor supply and wages.

Work from the past few years suggests 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 very close to the cross-sectional estimates found in other papers (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 on the order of around 20% (Blair

[3] I also perform the same analysis using simple cross-state variation similar to Kleiner and Soltas (2019) using the 2015-2018 CPS Outgoing Rotation Group and find similar results. To demonstrate the similarity in results, the main log wage regression coefficients are in Appendix Figure A10.

and Chung, 2019; Kleiner and Soltas, 2019), with some exceptions in occupations like nursing (DePasquale and Stange, 2016). On the other hand, licensed workers work more hours on the intensive margin (Bailey and Belfield, 2018; Kleiner and Soltas, 2019). In addition, the composition of workers shifts with licensing, with more women and black workers entering licensed occupations (Bailey and Belfield, 2018; Redbird, 2017), in part to take advantage of the signaling 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). Recertification can also lead to quality reductions in licensed sectors among migrants (Kugler and Sauer, 2005) due to the high opportunity costs of licensure among those with high ability.

On the topic of spillovers, a few important papers find notable effects of licensing requirements for particular occupations on complementary or substitutable occupations. Licensing and credentialing requirements for physical therapists, namely those which govern direct access to patients, has negative effects on the wages of occupational therapists because this service is substitutable between the two (Cai and Kleiner, 2016). When nurse practitioners, who act as a substitute for many services offered by physicians, are given broader scope for their practice, the wages of physicians are bid downward, while nurse practitioners' wages rise (Kleiner et al., 2016). Finally and most notably for the current paper, Kleiner and Park (2010) examine the effects of broadening the scope of practice for dental hygienists on the earnings and employment of dentists and hygienists. They find that as regulations allow hygienists to be self employed, wages for hygienists rise by 10 percent and employment 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 result in conditions similar to that of monopsony power in the labor market.

This paper contributes to this literature by identifying the broad effects of licensing on other occupations in the labor market. In particular, this paper is the first to demonstrate that the wage premium in licensed occupations, if generalized to more occupations, comes at a broad cost: lower labor market earnings for those in occupations that use similar skills, even when they may not directly perform similar functions. I am also the first to show that a pure labor supply shift does not fully explain these results, but that it is more likely that occupational licensing increases labor market rigidity and thereby exacerbates firm labor market power.

The remainder of the paper is organized as follows: Section 2 presents two competing frameworks for how barriers to entry may affect the labor market of other occupations; Section 3 explains the various datasets I use in my estimation; Section 4 presents the details of my occupational cluster technique (Section 4.1) and my border discontinuity design (Section 4.2); Section 5 describes the results; Section 6 discusses the results in light of the monopsony theory in Section 2; Section 7 concludes.

# 2 Two Frameworks for Barriers to Entry

## 2.1 Labor Supply with Skill Transferability

A host of papers present models of a competitive labor market in which barriers to entry into specific occupations will result in workers exiting 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.

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 shift 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.[4] 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.

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

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

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 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 $g$. $\gamma^{ij}$ 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 is 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 $K^j$, income in the current period $t$ in

[4]These can include any skills which make the individual suited for a set of occupations, like sociability, physical strength, cognitive ability, or leadership skills.

occupation $j$ can be expressed:

$$Y_t^j = E^s + r^j(C_{t-1}^j + \gamma^{ij} C_{t_j-1}^i) - c_t^j + \gamma^{ij} I_0^i + I_0^j \tag{2}$$

Here, $E^s$ is earnings capacity given formal schooling, and $r^j$ is a common rate of return to investments in $j$, while the $C$ cost parameters are at the individual level.

In present value terms, given discount rate $r$, an individual will switch occupations when:

$$\{\gamma^{ij} r^j C_{t-1}^j - r^i C_{t-1}^i + (\gamma^{ij} I_0^j - I_0^i)\} \sum_{g=t}^{T} (1/(1+r)^g)) < 0 \tag{3}$$

and when

$$\sum_{g=t}^{T} \sum_{h=t}^{g-1} \{(r^j c_h^j - c_g^j) - (r^i c_h^i - c_g^i)\}(1/(1+r)^g) \lesseqgtr 0 \tag{4}$$

Here, Equation 3 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 $\gamma^{ij}$.

Equation 4 is the difference in the value of future investment in occupation $j$ vs occupation $i$.

There are two key predictions of this model: 1) the greater the skill transferability, $\gamma^{ij}$, 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 in a few ways. A license which 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 true 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 which may be unrelated to the performance of the job.[5]

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, $j, h$. In terms of my setup, this implies that occupational licenses will push individuals in these groups out of licensed occupations in their skill cluster and into the most related occupations in the same cluster, increasing labor supply in a competitive market, and reducing wages. If, however, licensing is widespread enough, individuals may exit the cluster altogether. If this condition holds, wages in the cluster may rise.

This setup also predicts that those facing differential changes in costs with a new licensing requirement or who are categorically ineligible to work in a licensed occupation will be more responsive in their labor supply and therefore be the likely movers into the remaining unlicensed occupations. This might include women, who bear larger shares of home production responsibilities making occupational transition more costly, foreign-born Hispanic workers most affected by citizenship or residency requirements, or black workers, who are more likely than other racial groups to have a past incarceration on their record. This implies a composition shift among occupations in the skill cluster.

As a brief example of the mechanisms behind this framework, consider the rising licensing requirements to being a physical therapist or occupational therapist 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 and education requirements rise, other prospective entrants may then be deterred from entering either occupation and instead enter something like athletic training, which requires a bachelor's

[5] For example, Florida bill 851 requires 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).

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. If licensing requirements become more stringent in athletic training, many workers may exit this skill cluster entirely.

In summary, in this framework, the direction of wage and employment effects in occupations related to $i$ depends on whether licensing in proximity to $i$ is more likely to filter prospective entrants into an occupation *within* a cluster and thus increase overall employment or whether widespread licensing near to $i$ is sufficient to exclude individuals from entering the cluster in the first place. If within-cluster sorting dominates, labor supply will increase to related occupations and wages will fall. If cross-cluster sorting dominates, labor supply will decrease in the cluster (and individual occupations within it) and wages could rise.

## 2.2 Monopsony Framework

Counter to the prediction of rising (falling) labor supply and falling (rising) wages due to occupational licensing spillovers, there is an additional possibility of experiencing both a decline in overall labor supply into occupations close in skill content to a licensed occupation and falling wages. This possibility is suggested by 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 hygienists in a single market, but it is worth exploring further.

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 increases search costs, lowers reservation wages, and therefore increases monopsony power of the "unprejudiced" firms over black workers.

In my setting, a worker may search for a firm match across occupations, but costs rise as they search firm-occupation cells that are further away in skill content from their current occupation. 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). This effectively lowers the number of outside options available to each worker, raises their search cost, and lowers their reservation wage and/or their labor supply elasticity to the firm at the current wage. The result is an increase in monopsony power.

Following Black (1995), suppose there is a $\theta$ share of firms who, due to their product markets, will hire unlicensed workers with skills in cluster $S$, and (1-$\theta$) share who will hire licensed workers in skill area $S$. Those with a license, $l$, and those without, $n$, face wage offers from "unprejudiced" firms, $u$, of $\omega_u^l$ and $\omega_u^n$, while only licensed workers receive wage offers from "prejudiced" firms at $\omega_p^l$. Parameter $\alpha$ 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 $\kappa$ 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:

$$\kappa = \theta \int_{\alpha_p^l}^{\infty} (\omega_p^l + \alpha - u_r^l) f(\alpha) d\alpha + (1-\theta) \int_{\alpha_u^l}^{\infty} (\omega_u^l + \alpha - u_r^l) f(\alpha) d\alpha \tag{5}$$

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:

$$\frac{\kappa}{(1-\theta)} = \int_{\alpha^n}^{\infty} (\omega_u^n + \alpha - u_r^n) f(\alpha) d\alpha \tag{6}$$

An increase in the share of firms who only hire licensed workers in the skill cluster strictly increases the search cost and therefore lowers the reservation utility and 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.

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 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, per Blair and Chung (2018). In this case, the wage premium for obtaining a license will be higher for those demographic groups who obtain a license, while the wage penalty will be larger in the unlicensed sector for these groups.

Many licenses contain requirements that may differentially increase $\theta$ depending on demographic group. Again, requirements against incarceration may differentially affect 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 larger.

This framework predicts that as licensing increases within a cluster, wages in licensed occupations rise, while wages in the remaining occupations in the cluster fall. 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, as labor market concentration and monopsony power have been shown to be higher in smaller labor markets (Rinz, 2018). The prediction of composition changes is the same as the labor supply model.

# 3 Data

In order to test the relative strength of these models, 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, demographics, education, 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 tensions 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 fixed effects as 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 share of approximately 22 percent, consistent with other surveys (Blair and Chung, 2019) as well as other papers which use 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 who 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.[6]

[6] 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 to the state-occupation cell licensed in the NLD to that in the individual CPS data. The correlation 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 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.

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) who are 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.[7]

## 3.2 American Community Survey

To construct my border match sample, I use data from the 5% subsample of the American Community Survey with geographic identifiers for Public Use Microdata Areas (Steven et al., 2019) on or within 5 miles of each state border. 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.

One limitation of the ACS generally is the way in which 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 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).[8]

I limit my sample to those age 18-64 who are in the labor market and report positive

[7]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. 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 small, particularly in state-occupation cell of sizes larger than 10. Because clusters are larger than occupations, finite-sample bias is even less of a concern for these measures.

[8]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.

weekly earnings. Following Gittleman et al. (2018); 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.[9] As seen in Table 2, 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, with the exception of the share of the population that is Hispanic, Asian or Pacific Islander, and the share that is foreign born, as well as a small difference in the share with a Bachelor's degree. This may primarily driven by the exclusion of parts of coastal California which have highly concentrated Asian and Hispanic populations as well as cities in middle and southern Texas. Importantly, these sample areas are very similar in terms of their licensed shares, both within the focal occupation, and within clusters.[10]

## 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 as well as 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 on a variety of measurements, education, 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 (Autor and Dorn, 2013; Autor, 2014). These are:

1. Non-routine cognitive/analytical

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

[10] There is a similar difference in the border designs 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 A10) suggests the treatment effects are similar.

2. Non-routine cognitive/interpersonal
3. Routine cognitive
4. Routine manual
5. Non-routine manual/physical
6. Non-routine interpersonal adaptability

These skills capture important characteristics about each occupation which 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 numbers to create a weighted average of these O*NET skill characteristics at the 2010 Census occupation level to match the occupation categories of the CPS licensing numbers. The final figure is an 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.

# 4 Empirical Approach

## 4.1 Occupation Clustering

In order to classify occupations into similar groups, I consult the literature on data clustering techniques. While there are dozens of algorithms and approaches from which to choose, I focus on hierarchical agglomerative clustering (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 clusters as the algorithm moves up the hierarchy. The nearest clusters are merged if their distance is the smallest among remaining clusters and occupations. Eventually, every occupation will be grouped in a single cluster, forming 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 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.[11] This makes HAC a notable improvement over other popular approaches like K-means clustering or DBSCAN clustering.

Figure 1 presents a toy example of HAC. The left pane represents datapoints 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 points (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 like 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 widely used technique in mind, I pursue the following steps:

[11] 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 distinction on broader latent skills makes clusters surrounding these occupations very dense.

First, I calculate the correlative distance between each occupation across these six occupational skill characteristics as well as the median log wage for each occupation.[12] 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. In forming the clusters, I use average linkage distance, which uses the mean data value of distance between all points in the cluster when selecting the nearest cluster to merge. Unlike measures such as "single" or "complete" linkages, which, respectively, use the nearest or the furthest unit of the cluster to calculate distances, the average linkage approach is more robust to outliers within clusters.

Third, I calculate a data-driven "optimal" number of clusters from which to base my calculations. 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). The first two measures are based on maximizing their validation measure, while the latter two are based on minimizing their validation measure.

Under these validation measures, the optimal number of clusters appears to be in the 13-20 range, although there is not a completely clear consensus across measures. Figure 2 shows the results using these four validation measures. Panel A suggests that the optimal number of clusters is likely below 18, as the index bottoms out above this number, but it markedly higher at lower numbers of clusters. Panel B 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 on the totality of these

[12]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 very similar physical and cognitive skills, the returns to these may differ dramatically.

tests, there is considerable overlap in the optimal number from the mid-teens to twenty.

Rather than choosing a single number of clusters as the optimum, I calculate and plot a range of estimates across the number of clusters from 4 to 20 in order to transparently report the coefficients of interest under larger, less compact clusters (4) relative to smaller, more compact clusters (20). 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 may also fall.[13]

As an eye test on cluster assignments, I present the top five most frequent occupations in each cluster at their most compact (20 clusters) in Appendix Table A1.[14] 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 and waitresses, though they are separated by industry definitions. Police detectives and private investigators use very 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 Discontinuity Design

In the experimental ideal, a researcher choosing to study the effects of licensing on the labor market would randomly assigning some occupations in some jurisdictions and clusters to impose a licensing requirement, while others remain unlicensed. In order to approximate this experimental ideal, I construct a matched border sample of PUMAs with contact with a common state border and include state, occupation, and border fixed effects, as expressed

[13]In my estimates, treatment effects above approximately ten clusters are robust to increasing the number of clusters and consistent across my outcomes of interest.

[14]Not all clusters have five occupations within them depending on their skill distance from other clusters and compactness within clusters.

in:

$$y_{iocms} = \beta_0 + \beta_1 LicensedShare_{os} + \beta_2 LicensedShare_{cs}^{-o} + X'\beta_3 + \delta_o + \gamma_s + \tau_m + \varepsilon_{iocms} \quad (7)$$

This equation characterizes outcome $y$ for individual $i$ in occupation $o$ in cluster $c$ in state $s$ on the state-state border $m$.[15] $\beta_1$ captures the wage effect of licensing individual $i$'s entire *own* occupation category on the wage of individuals in occupation $o$, whereas $\beta_2$ captures the effect of fully licensing all other workers in cluster $c$ *outside* of occupation $o$ (the focal occupation). 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 being age 18-25. $X$ is a set of individual controls for sex, race/ethnicity, age, and age squared.[16]

Rather than relying purely on the assumption of state-wide similarity in labor markets across licensing status, the border discontinuity design compares two workers in the same occupation on two sides of a state border where the state line creates differences in their occupational licensing status or the status of other occupations in their skill cluster, while holding constant the shared features of the local labor market as well as other attributes of their state such as minimum wage laws.[17]

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-

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

[16]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.

[17]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 this specification, identification comes purely from PUMAs which share borders with multiple states. Results from both exercises show that my border design is robust to unobserved characteristics of the local labor market.

MD —contribute to identification of the effects of licensure for each occupation.[18] In this design, unobserved characteristics of local labor markets which may affect employment and wages are absorbed in the border fixed effect, and, conditional on this fixed effect, licensing shares are arguably exogenous.

One concern about a border discontinuity design of this nature is the possibility of spatial spillovers. If individuals move across the state border to avoid occupational regulations, this should bias my estimates of the labor market effects of licensure towards zero. However, 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). Labor market size is a particularly important measure, as monopsony theory suggests that smaller labor markets experience greater labor market concentration (Rinz, 2018).

To examine the overall employment effects of licenses and license spillovers, I also include log employment in the occupation-PUMA cell as an outcome variable and run the same specification excluding individual characteristics. I also estimate each occupation's log share of cluster-PUMA cell employment as a measure of within-cluster sorting. The own-occupation effect ($\beta_1$) measures the effects of licensure on employment in that occupation itself, while $\beta_2$ captures the employment spillovers. A pure labor supply explanation predicts a positive coefficient for overall employment and within-cluster share of employment. A negative spillover coefficient on overall employment in the focal occupation is suggestive of monopsony power if earnings effects are negative.

[18]Many studies use this approach, including in the occupational licensing literature (Blair and Chung, 2019; Black, 1999).

# 5 Results

## 5.1 Earnings Premium and Spillovers

Examining the overall earnings effects of widespread occupational licensure, Figure 3 indicates that having a license for one's own occupation leads to a earnings premium of approximately 10%, a finding consistent with 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 by 2-2.5% on average. I can rule out effects as small as .8-1% and effects larger than 4%. Given that the validated optimum number of clusters is somewhere in the 13-20 range, the effects appear concentrated around 2%.[19]

I find substantial heterogeneity in this effect across gender as well as race/ethnicity and nativity. My findings for the own-occupation licensing premium are consistent with other findings which use the SIPP's occupational licensing topical module (Blair and Chung, 2018) wherein licenses may signal ability in such as way to overcome the effects of statistical discrimination.

Figure 4 reveals that, while women receive a larger earnings premium than men, they also experience a larger earnings spillover penalty. For women, increasing skill cluster licensing requirements by 10 percentage points leads to a reduction in wages of approximately 3%, while the same coefficient is less than 2% for men. According to Figure 5, Non-Hispanic black workers as well as Hispanic workers experience larger earnings spillovers than their Non-Hispanic white counterparts. Point estimates for Hispanic workers are consistently around -3% for a ten percentage point increase in cluster licensure compared to -2% for Non-Hispanic white workers. Non-Hispanic black workers experience the largest penalty, with point estimates in the 3.5-4% range. The large relative penalty for Non-Hispanic black workers may be due to licensing requirements which prohibit those who have been incarcerated from obtaining a

[19]Throughout these results, 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.

license, an idea explored by Blair and Chung (2018; 2019). As licenses which exclude those who have been incarcerated increase, the set of occupations in which someone who with a set of latent skills who has been incarcerated may work narrows. The returns to obtaining a license as an ability signal may be higher in this case.

Most of the effect on Hispanic workers appears to be driven by foreign-born Hispanic workers. Figure 6 indicates that there is essentially no wage 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 all larger than 3% compared to less than 2% for native-born Hispanic workers. Given the young age, relatively low educational attainment, and migrant status of foreign-born Hispanic workers, these effects are in line with expectations. In particular, citizenship or permanent residency requirements for many licenses may preclude many foreign-born Hispanic workers from entering a variety of occupations, which severely limits their set of choices. Both a direct labor supply effect into unlicensed occupation and a monopsony effect could explain this difference, as the threat of leaving a firm to pursue another job or another occupation may be severely limited by concerns about legal work status.

Given the presence of possible statistical discrimination against Non-Hispanic black workers in light of their disproportionate experience with incarceration 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. Figure 7 indicates that this is, indeed, the case. Native-born black workers experience spillovers of 3-4% with a ten percentage point increase in cluster licensure, while foreign-born black workers experience spillover effects of 4-5%.[20]

[20] 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.

Figure 8 shows that there is a clear relationship between the intensity of the negative spillover effects and labor market size. The largest labor markets essentially show no relationship between licensing and earnings, while for the other three quartiles, this relationship intensifies as market size declines. In the smallest labor markets, the earnings effect is as large as -4% compared to -2% in quartile three for a 10 percentage point increase in licensure. The own-occupation wage premium, however, remains the same in all three of the bottom quartiles.

### 5.2 Composition Effects

In addition to direct earnings effects, licensing spillovers may shift the distribution of workers within occupations in terms of their 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. For simplicity, I plot the coefficients and standard errors for within-cluster spillovers set at 20 clusters.

Figure 9 indicates 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 degrees fall by .75 percentage points with a 10 percentage point increase in clusterwide licensure outside the focal occupation. Relatedly, the share of workers in the focal occupation that are 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 are Hispanic or born outside the US by .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 high school graduates or those without a college degree shifting into the remaining unlicensed occupations, although advanced degrees do decline. It does not appear that shifting human capital, per se, is responsible for the decline in wages. 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

In order to understand the other mechanisms underlying the wage effects I observe, I estimate a border match model of log employment within each occupation-PUMA cell. I also estimate my models using each occupation's log share of cluster-PUMA cell employment as an additional outcome to capture within-cluster sorting.

Figure 10 indicates that overall employment in each occupation falls by approximately 15 percent when the occupation is fully licensed. However, as licensure increases across the cluster, overall employment in the focal occupation *falls* by 10-15 percent with a ten percentage point increase in clusterwide licensing requirements. In their choice of occupation, prospective workers may be deterred by widespread licensing rules from entering a cluster, even with large skill transferability, because entry costs are so high.

After entering the cluster, workers appear to sort into the remaining occupations. Figure 11 indicates that as an occupation becomes fully licensed, its share of cluster employment falls by approximately 10 percent, consistent with the overall employment effects in Figure 10. The spillover coefficients indicate that there is a small effect of widespread licensing rules on sorting into the focal occupation. At 16-20 clusters, the share of cluster employment in the focal occupation rises by approximately 3-7 percent when clusterwide licensing increases by 10 percentage points, though I cannot rule out very small effects.

Like the wage effects discussed previously, the employment effects differ widely across labor market size. Figure 12 shows that the negative coefficients on log employment in the focal occupation are particularly pronounced in smaller labor markets. The effect is -20% in the smallest labor markets, compared to zero for the largest. At the same time, the negative own-occupation license effect is largest for the larger labor markets.

Taken together, these results indicate that widespread licensing in a skill cluster may lead to small increases in the *share* of workers in the focal occupation, but that this increase in share is not enough to overcome the negative overall effects of licensing on entry into the cluster. Overall labor supply into the focal occupation is still strongly negative, particularly in smaller labor markets.

The strong negative employment *and* earnings effects of licensing spillovers appears suggestive of monopsony, which I discuss in Section 6.

## 5.4 Robustness Checks

As a test that unobserved characteristics of the local labor market (PUMA) 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 which border multiple states. Appendix Figures A1, A2, and A3 show these results for the overall estimate, by sex, and by race/ethnicity, respectively. These estimates are extremely close to 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 wage 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 A4 indicates that the overall wage estimates are not sensitive to any particular cluster. For two of the clusters, my estimates fall from -.2 to -.15, though the difference is not statistically significant. For these tests by gender and race/ethnicity, see Appendix Figures A5 and A6.[21]

[21]These show some sensitivity within Clusters 1 and 12. Cluster 12 includes cashiers, housekeepers, and

I also show the employment effects regressions in this same format in Figure A7. This exercise indicates that the within-cluster sorting behavior attributable to one's own occupation being licensed appears primarily driven by Cluster 1, which is the largest cluster in terms of the number of occupations and contains various managers, K-12 teachers, and other advanced professionals. This cluster is highly licensed. The spillover effects, however, are consistent across eliminating any particular clusters. The effects on total log employment, while slightly sensitive to the exclusion of Cluster 1, are not statistically significantly different.

# 6 Discussion

The pattern of lower wages and lower employment in the focal occupation as a result of clusterwide 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 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 which explores the use of wider definitions of a "local labor market" for workers in the measurement of monopsony power and concludes as outside occupations become more feasible to enter, wages rise in one's own occupation if related occupations experience wage increases (Schubert et al., 2019). In contrast, 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

food prep workers, which employ at outsized share of Hispanics and Non-Hispanic black workers.

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.[22]

The literature also suggests that immigrants supply labor to the firm much less elastically than their native-born counterparts, leading to a predicted 7% wage penalty on average (Hirsch and Jahn, 2015). 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). Switching costs may be lower in large labor markets because of the physical proximity of available jobs and a wide set of available choices from which a worker may choose. Relatedly, smaller labor markets may also imply a smaller product market. 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).

[22]This also may be related to the fact that women generally perform more non-routine, cognitive work than men on average, and non-routine cognitive work appears more exposed to monopsonistic behavior by firms (Bachmann et al., 2019).

# 7 Conclusion

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

At the same time, raising barriers to entry across more and more occupations may have its own unintended consequences. This analysis suggests that as licensing grows, workers who might otherwise choose to work in an occupation but for the costs of obtaining a license may be worse off and that these effects are most keenly felt by workers already more likely to be vulnerable. If all other workers in an occupation's skill cluster are licensed, my estimates imply negative wage effects on the order of 20%, with some effects for minority workers of almost 40%.

The employment and earnings effects of these regulations, if broadened to include more occupations, may lead to labor market conditions similar to that of a monopsonist. In that case, while licensed workers are better off, unlicensed workers face fewer opportunities for advancement and are unambiguously worse off due to these costly restrictions. In the long run, policymakers should weigh the public health and safety justifications for occupational licensing against the possible negative labor market effects of these regulations on workers who may not be party to the negotiations between the political entities involved.

While the analysis presented here shows significantly lower labor supply 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 influenced by monopsony power. Without firm-level data in geographic markets, I cannot directly test the relationship between labor market power and licensing statutes. Further work in this area may attempt to test the effects of changes in occupational licensing statues and labor market power in particular industries or occupations.

In addition, 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.

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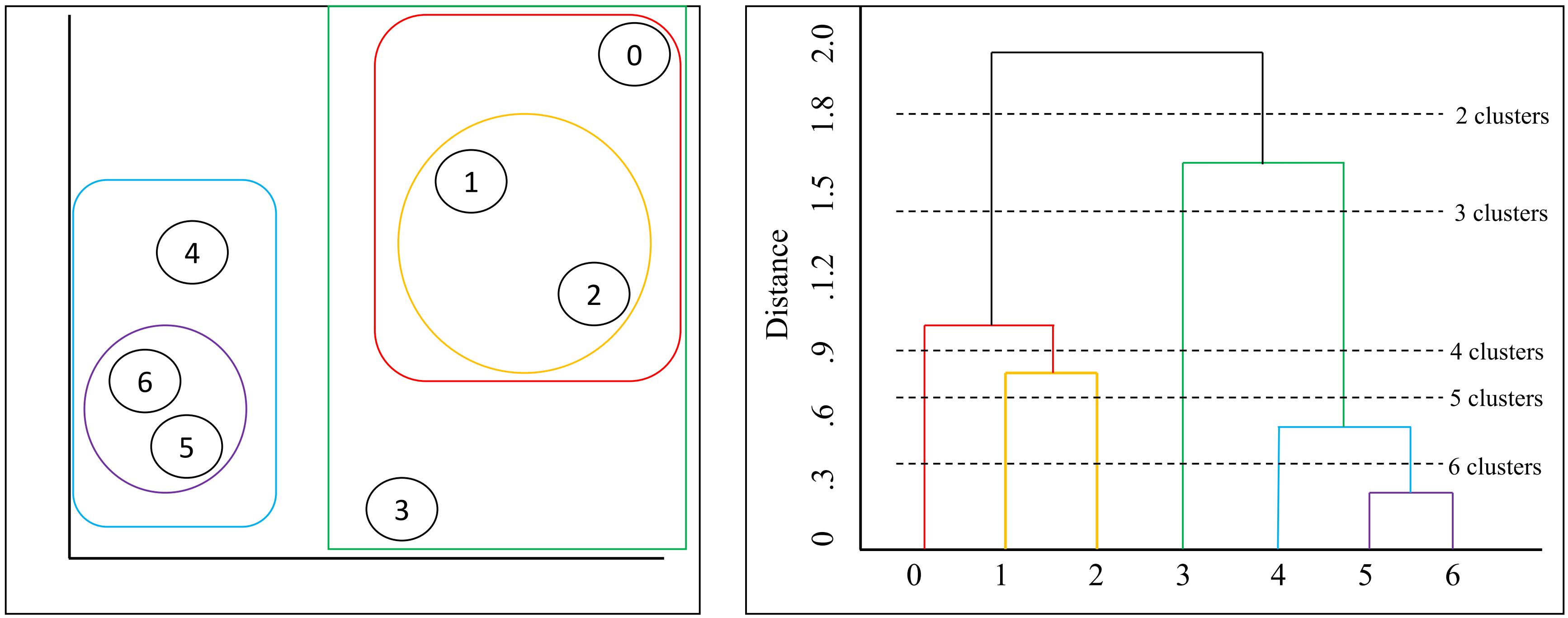
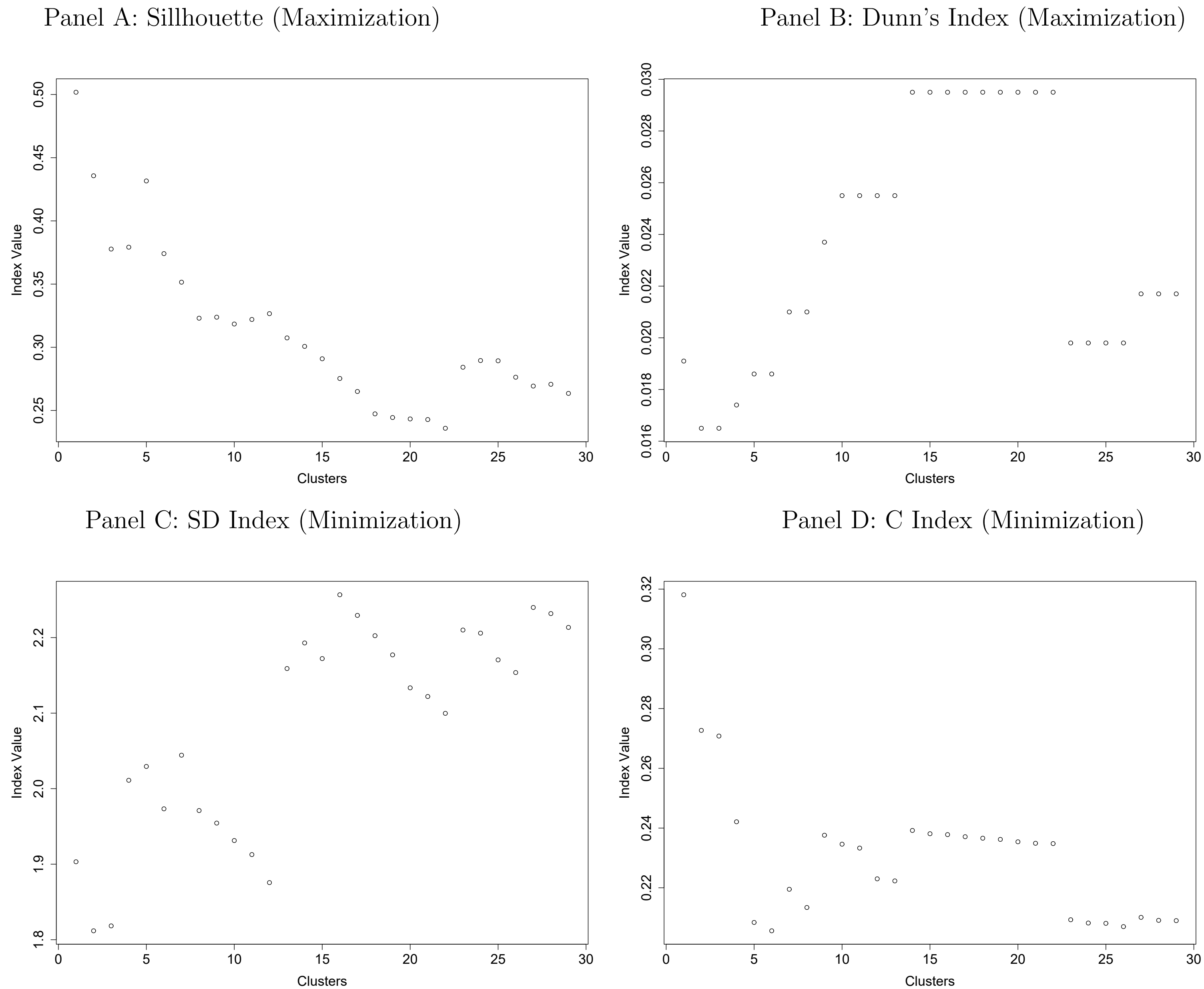
# Figures

Figure 1: 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 2: Cluster Validation Exercises

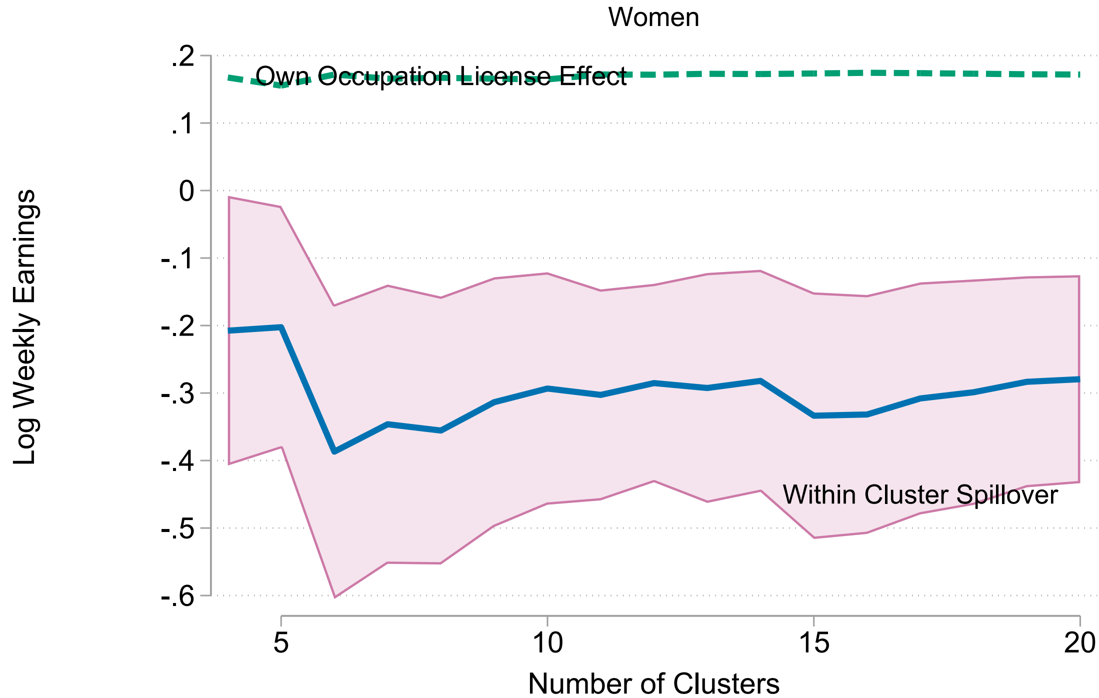



Source: Author's calculations of O*NET skills data following six skills in Acemoglu and Autor (2011) and median log wage.
Note: Clusters are generated using the HAC approach detailed in section 4.1.

Figure 3: 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 7. 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.

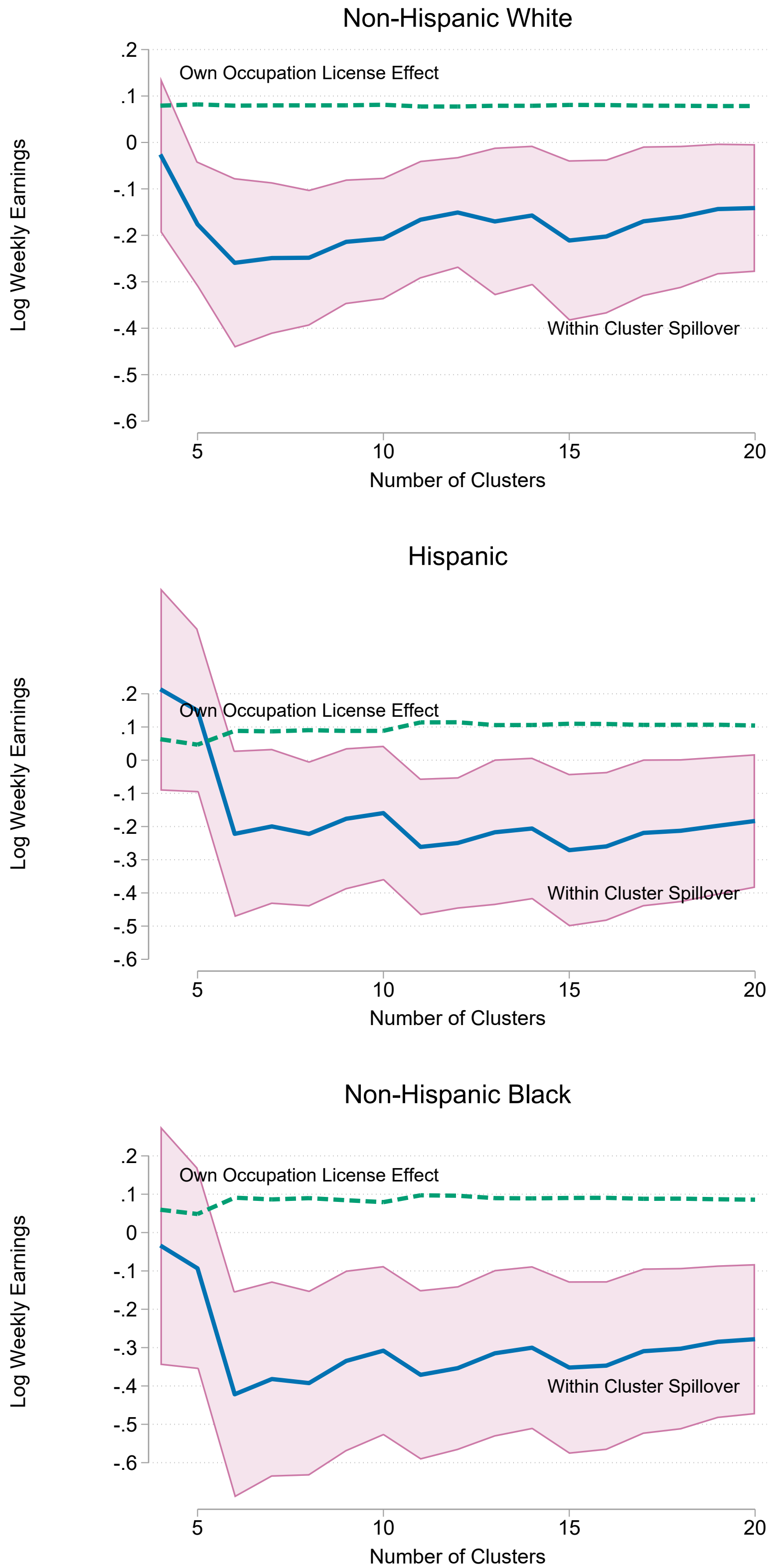
Figure 4: Coefficients of Log Weekly Earnings by Number of Clusters, by Gender





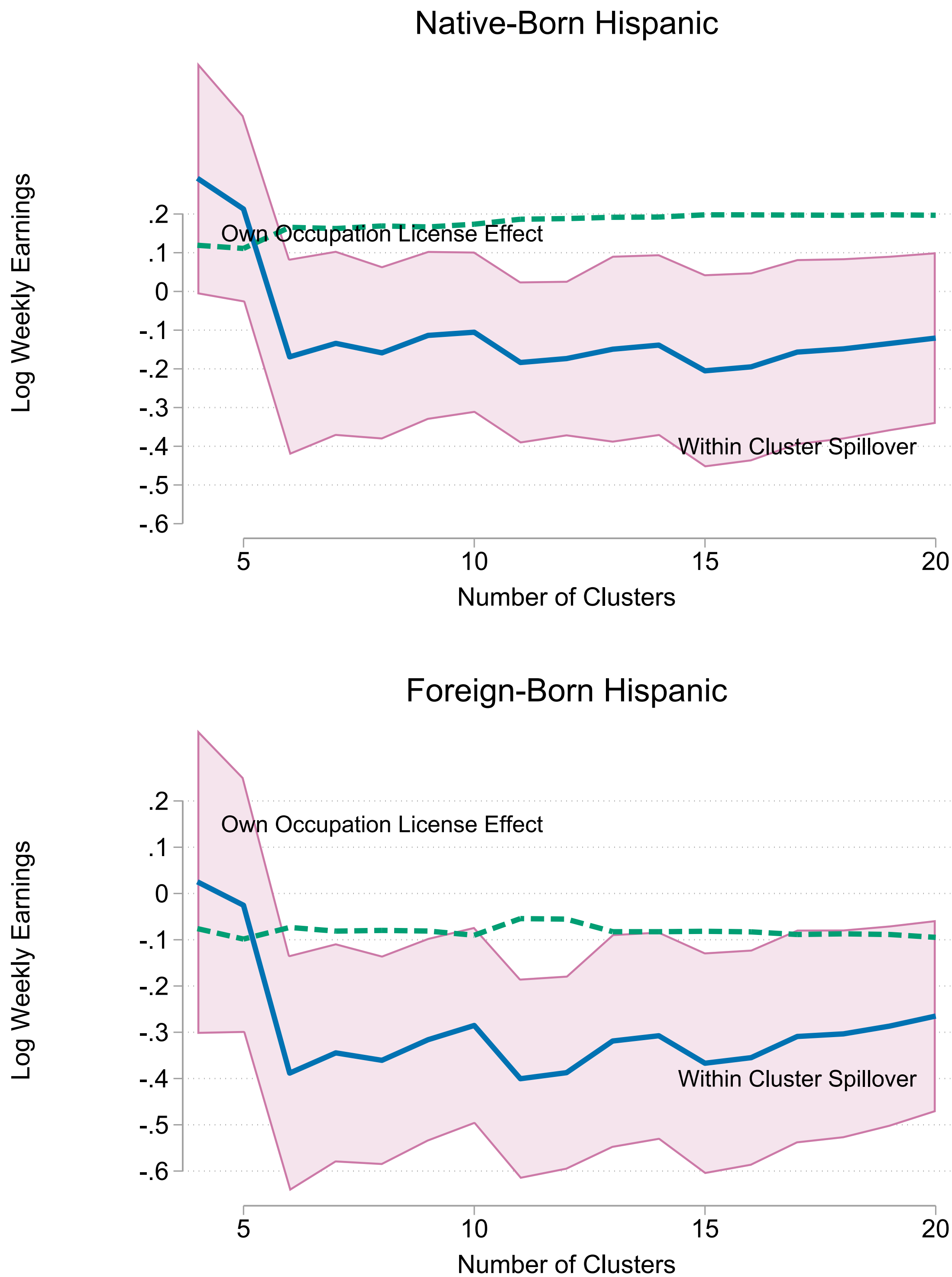
Source: Author's calculations of ACS, O*NET, and CPS licensing data.
Note: Coefficients are generated from the border match design detailed in Equation 7. Standard errors are clustered at the occupation level. 95% confidence intervals in red. Spillover coefficients are based on 100% licensure of an occupation's cluster outside their own occupation.

Figure 5: Coefficients of Log Weekly Earnings by Number of Clusters, by Race/Ethnicity



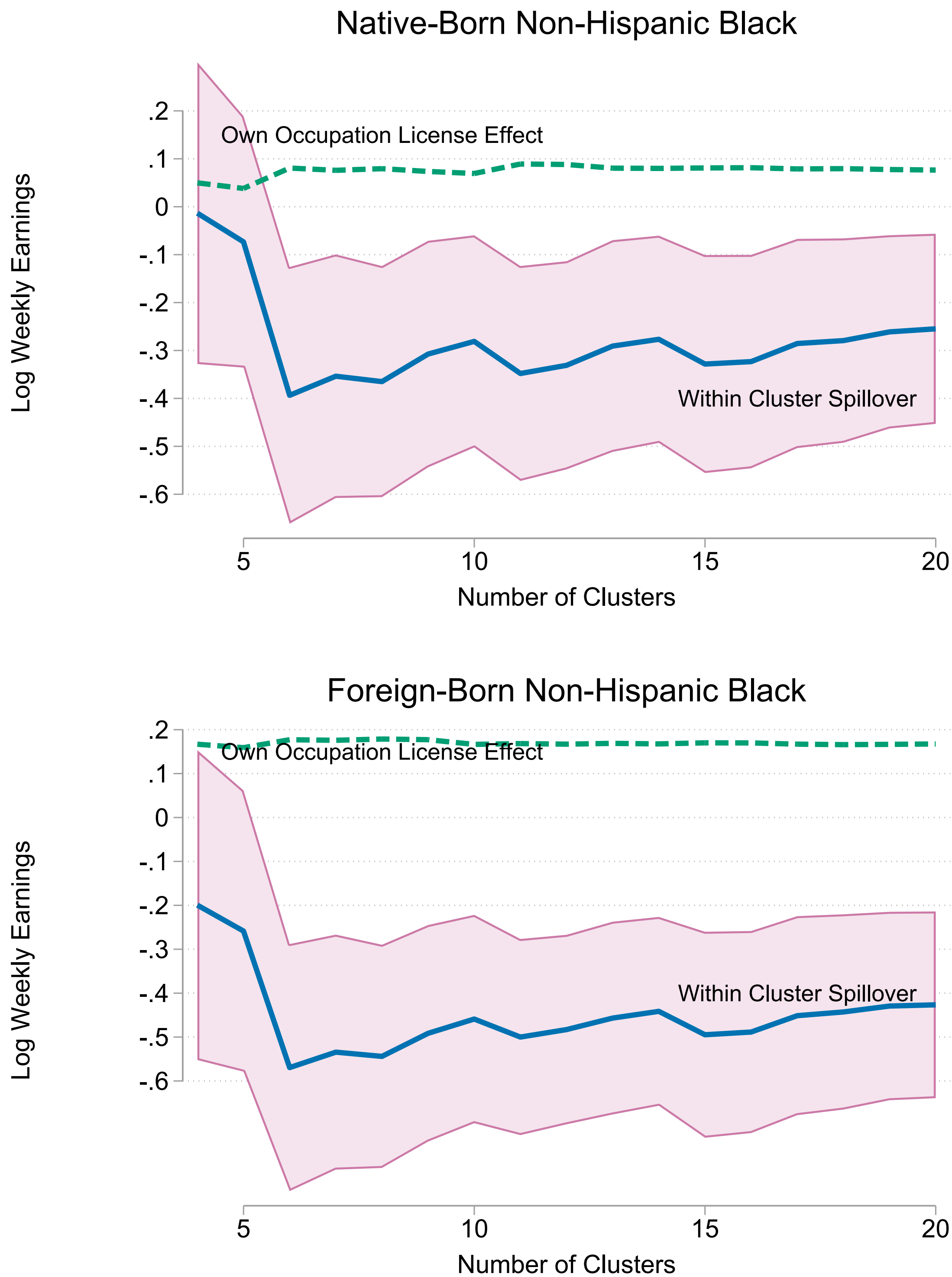

Source: Author's calculations of ACS, O*NET, and CPS licensing data.
Note: Coefficients are generated from the border match design detailed in Equation 7. Standard errors are clustered at the occupation level. 95% confidence intervals in red. Spillover coefficients are based on 100% licensure of an occupation's cluster outside their own occupation.

Figure 6: Coefficients of Log Weekly Earnings by Number of Clusters,
Hispanic Workers by Nativity



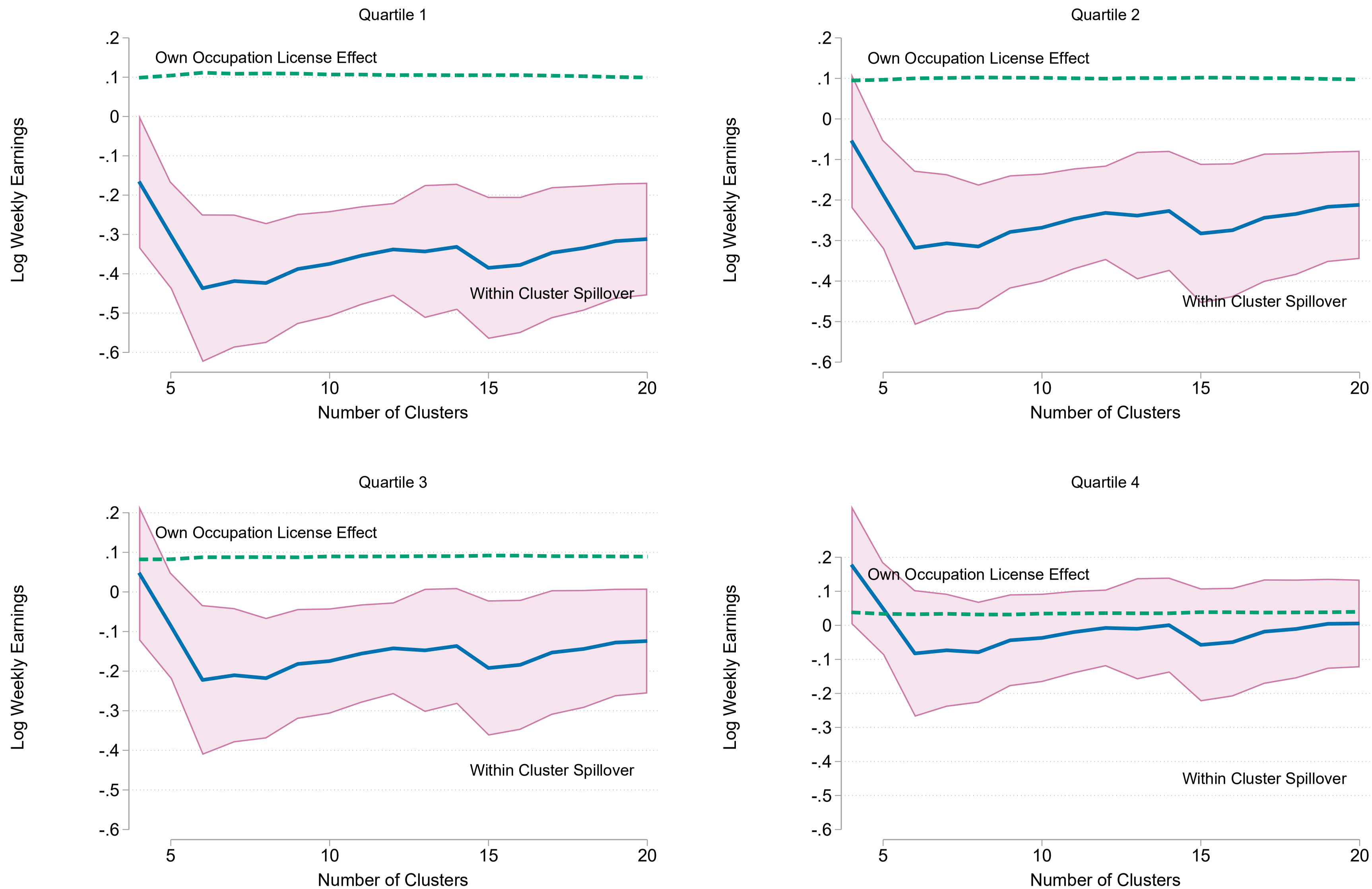

Source: Author's calculations of ACS, O*NET, and CPS licensing data.
Note: Coefficients are generated from the border match design detailed in Equation 7. Standard errors are clustered at the occupation level. 95% confidence intervals in red. Spillover coefficients are based on 100% licensure of an occupation's cluster outside their own occupation.

Figure 7: Coefficients of Log Weekly Earnings by Number of Clusters,
Non-Hispanic Black Workers by Nativity



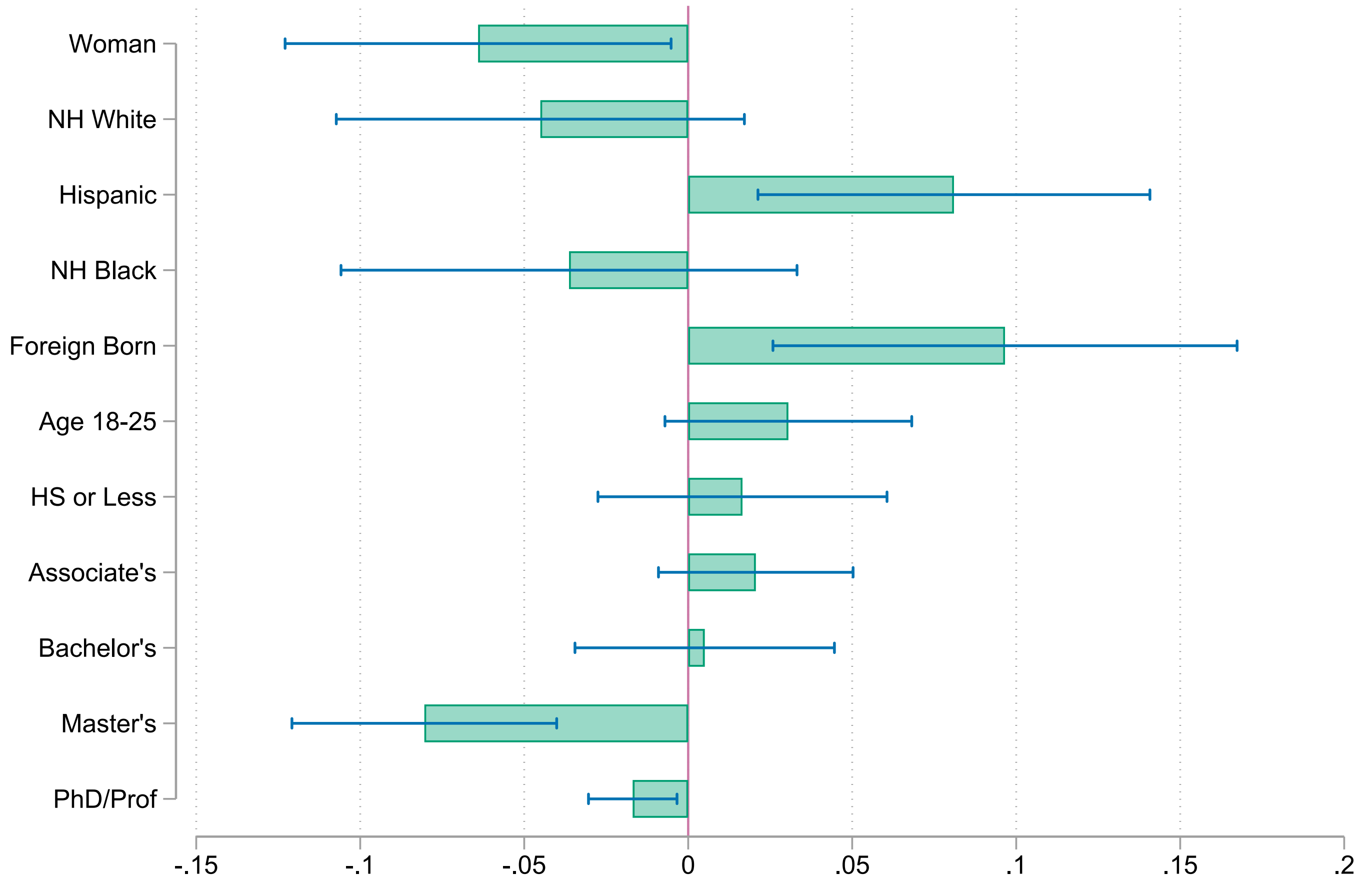

Source: Author's calculations of ACS, O*NET, and CPS licensing data.
Note: Coefficients are generated from the border match design detailed in Equation 7. Standard errors are clustered at the occupation level. 95% confidence intervals in red. Spillover coefficients are based on 100% licensure of an occupation's cluster outside their own occupation.

Figure 8: Coefficients of Log Weekly Earnings by Number of Clusters,
By PUMA Size Quartile



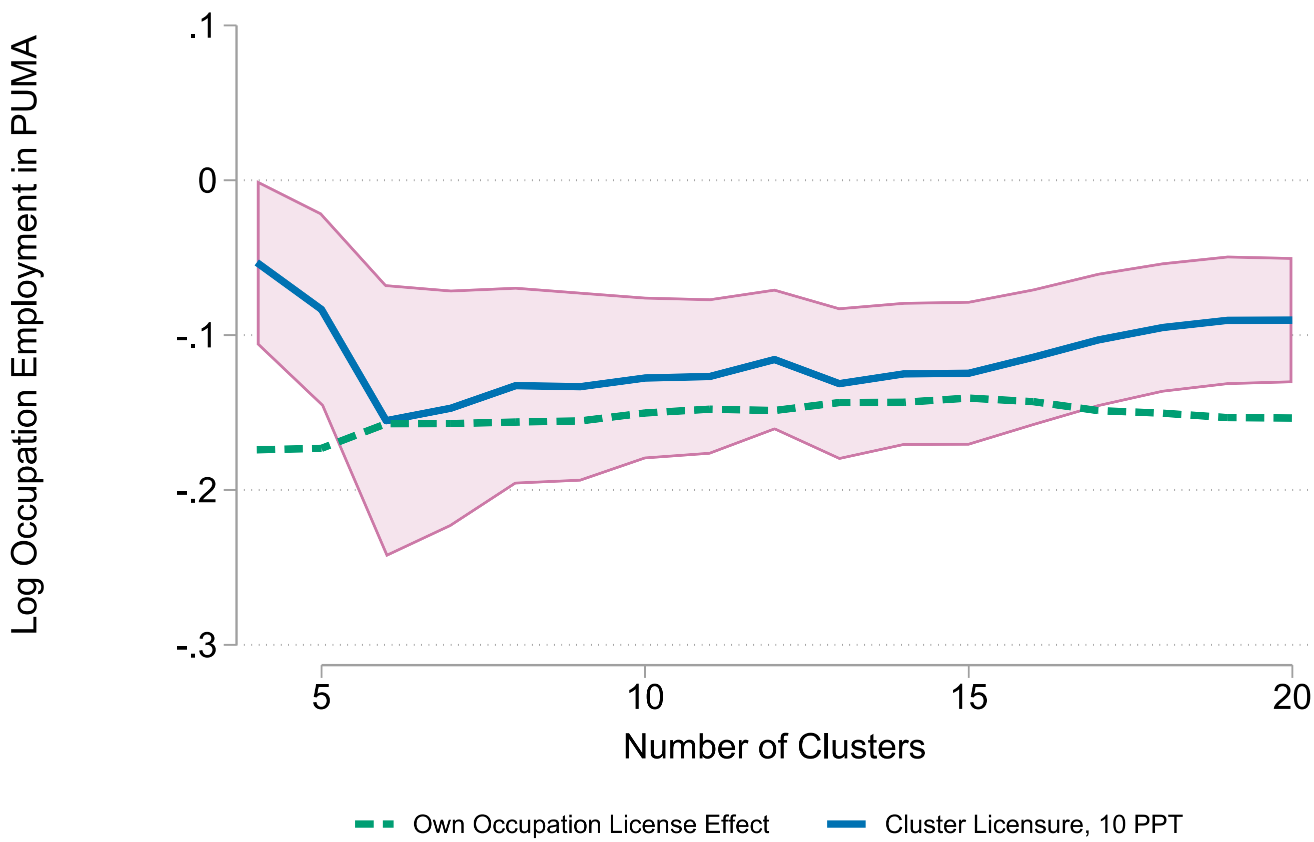

Source: Author's calculations of ACS, O*NET, and CPS licensing data.
Note: Coefficients are generated from the border match design detailed in Equation 7. Standard errors are clustered at the occupation level. 95% confidence intervals in red. Spillover coefficients are based on 100% licensure of an occupation's cluster outside their own occupation.

Figure 9: Composition Effects of Licensing Spillovers, 20 Clusters



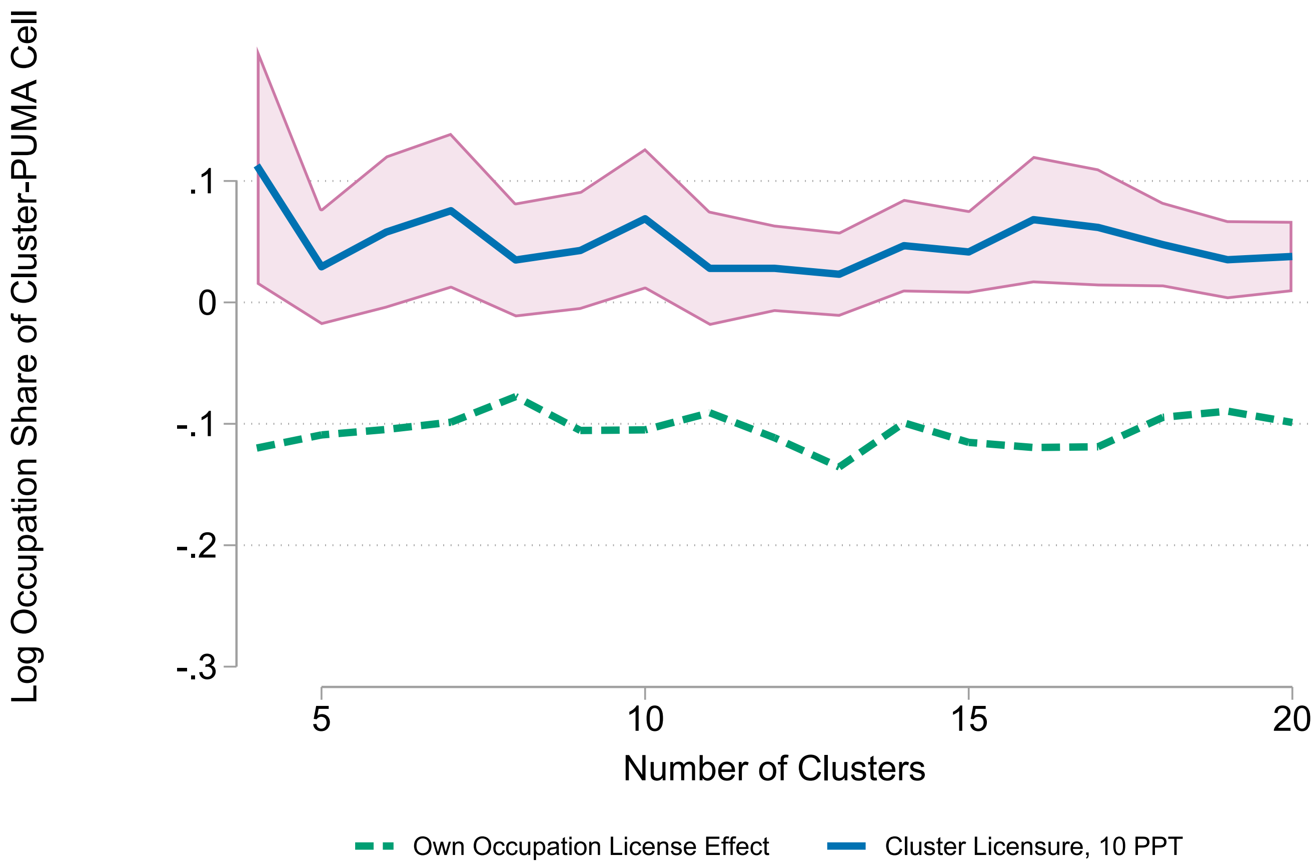

Source: Author's calculations of ACS, O*NET, and CPS licensing data.
Note: Coefficients are generated from the border match design detailed in Equation 7 for linear probability models on binary outcomes. Standard errors are clustered at the occupation level. Spillover coefficients are based on 100% licensure of an occupation's cluster outside their own occupation for 20 total defined clusters.

Figure 10: Employment Effects of Licensing Spillovers by Number of Clusters



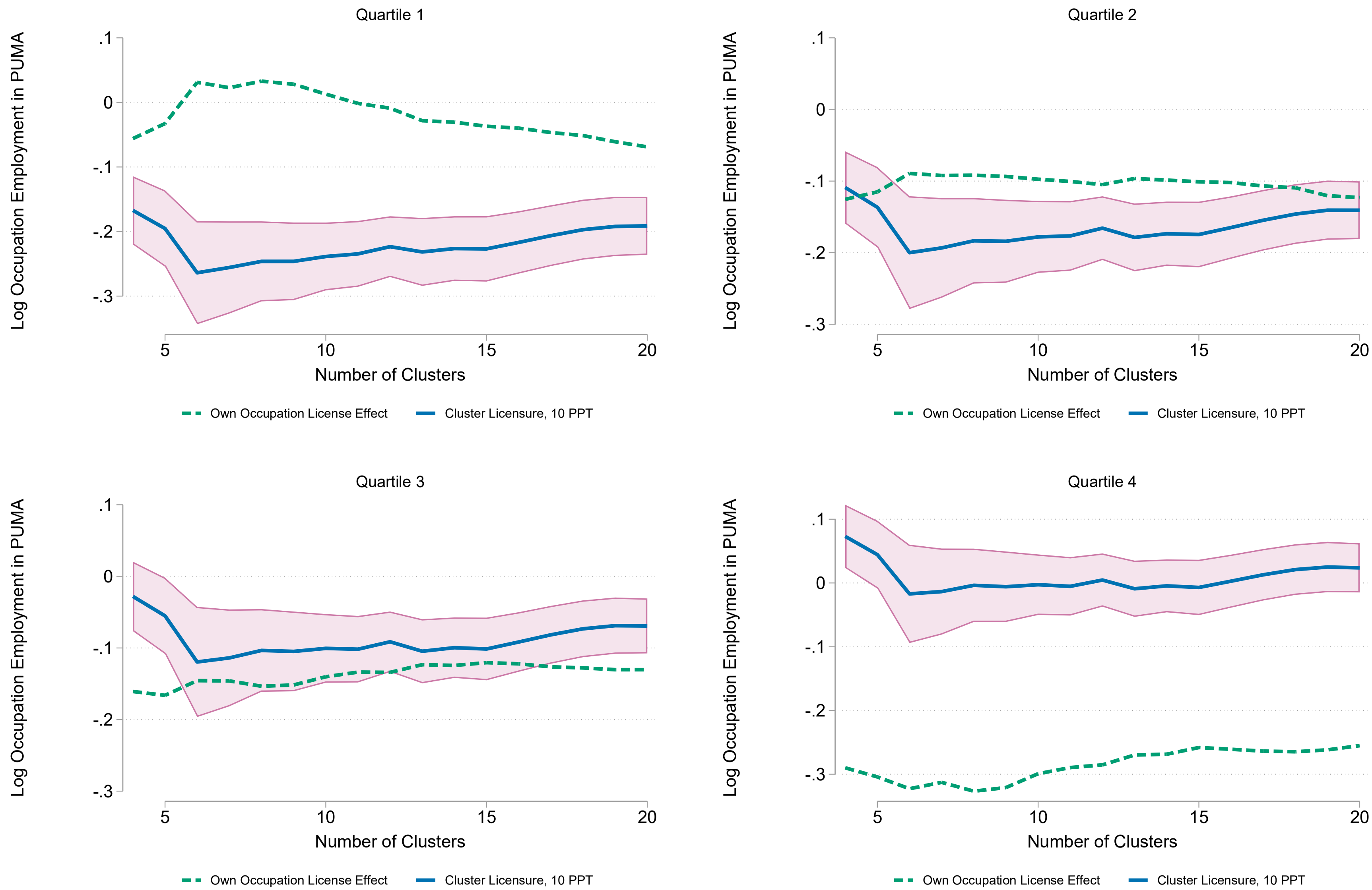

Source: Author's calculations of ACS, O*NET, and CPS licensing data.
Note: Coefficients are generated from the border match design detailed in Equation 7. Standard errors are clustered at the occupation level. 95% confidence intervals in red. To better scale, spillover coefficients are based on 10 percentage point increase in licensure of an occupation's cluster outside their own occupation.

Figure 11: Employment Sorting 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 7. Standard errors are clustered at the occupation level. 95% confidence intervals in red. To better scale, spillover coefficients are based on 10 percentage point increase licensure of an occupation's cluster outside their own occupation.

Figure 12: Coefficients of Log 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 7. Standard errors are clustered at the occupation level. 95% confidence intervals in red. Spillover coefficients are based on 10% licensure of an occupation's cluster outside their own occupation.

# Tables

Table 1: Components of Latent Skill Measurements

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

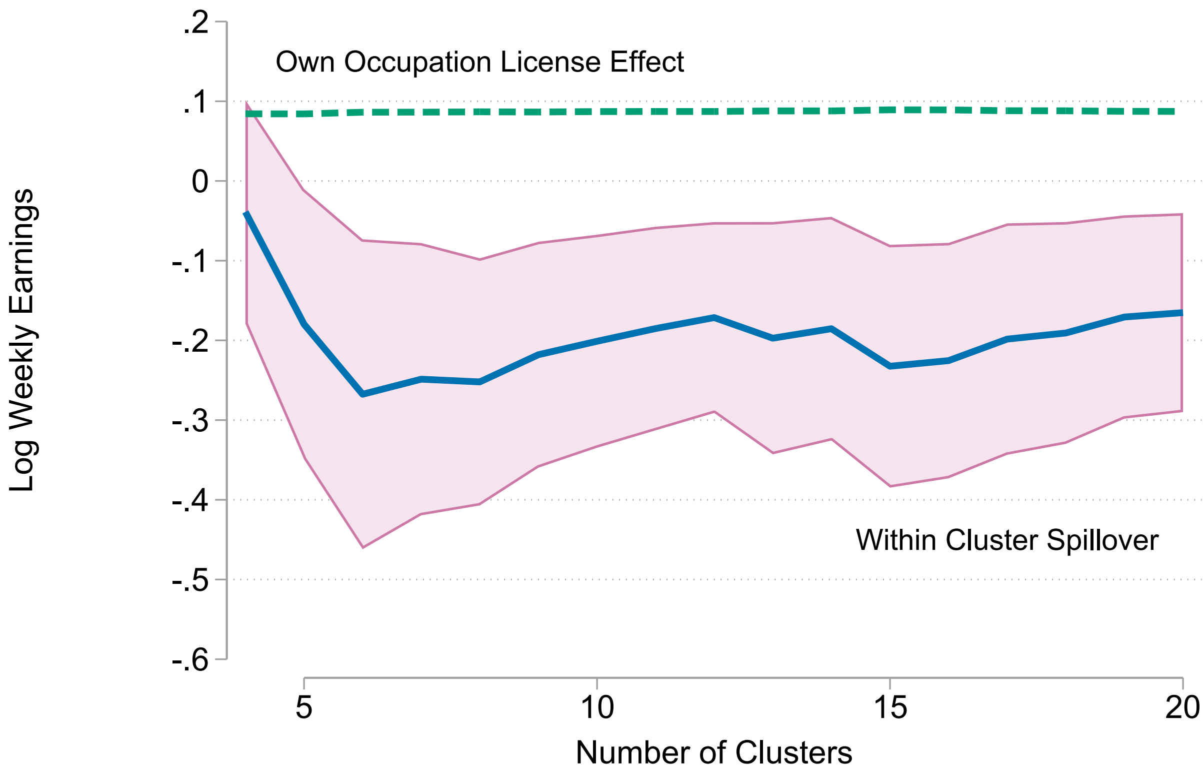
Table 2: Summary Statistics by Sample

| | 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 Occupation | 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.

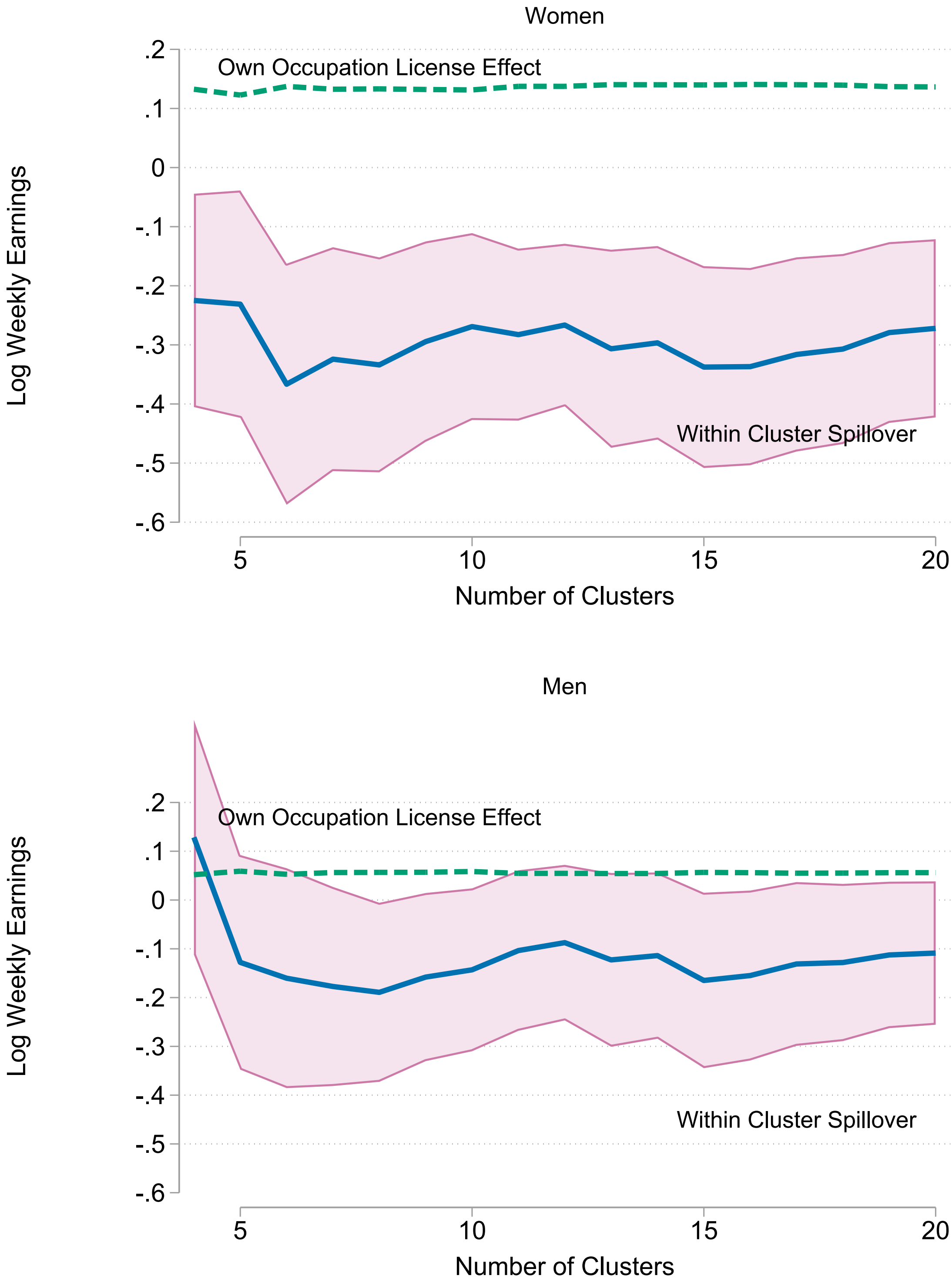
# A Figures and Tables Appendix

Figure A1: Coefficients of Log Weekly Earnings by Number of Clusters
All Occupations, Adding PUMA FE



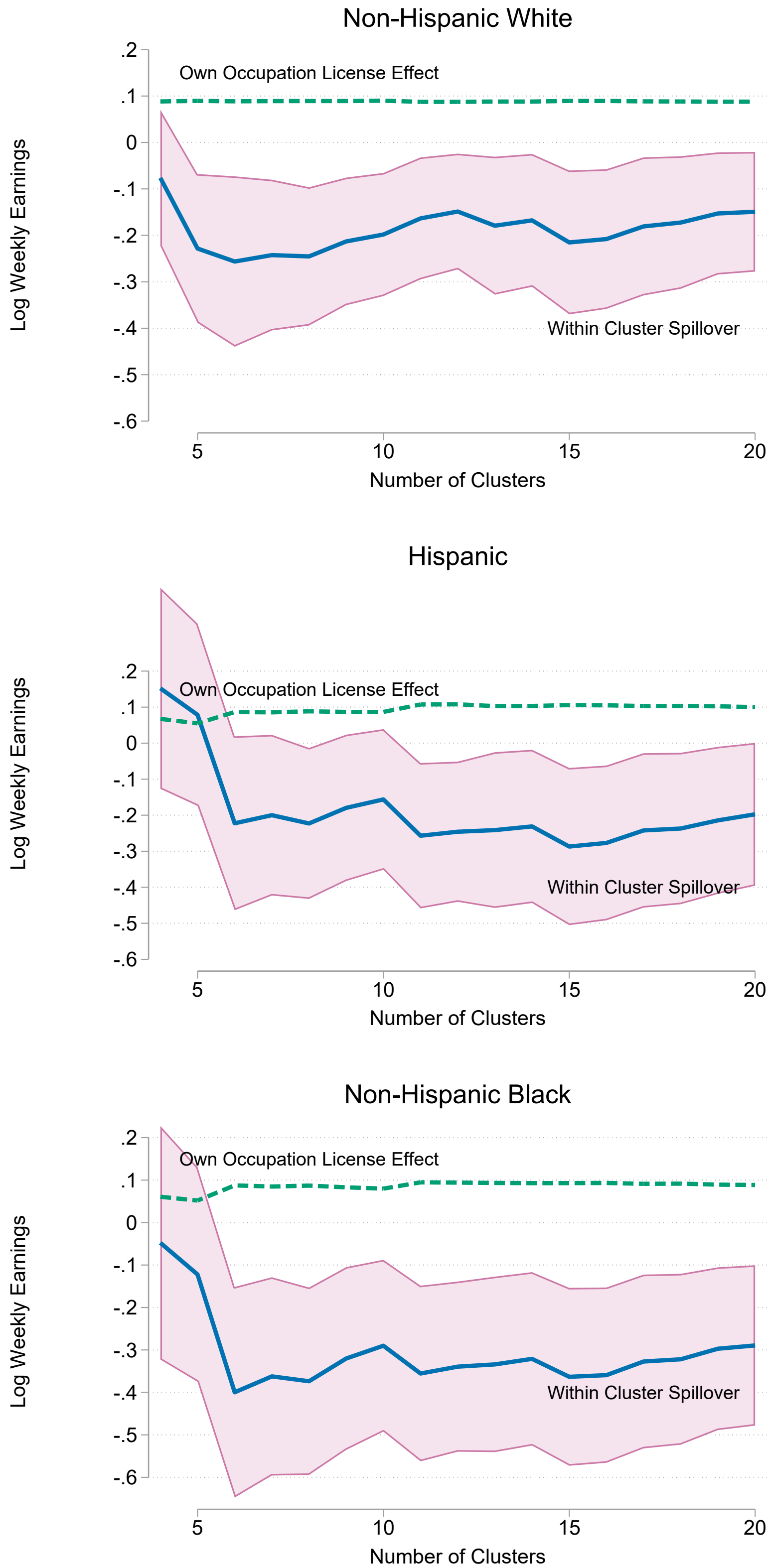

Source: Author's calculations of ACS, O*NET, and CPS licensing data.
Note: Coefficients are generated from the border match design detailed in Equation 7. Standard errors are clustered at the occupation level. 95% confidence intervals in red. Spillover coefficients are based on 100% licensure of an occupation's cluster outside their own occupation.

Figure A2: Coefficients of Log Weekly Earnings by Number of Clusters, by Gender
All Occupations, Adding PUMA FE



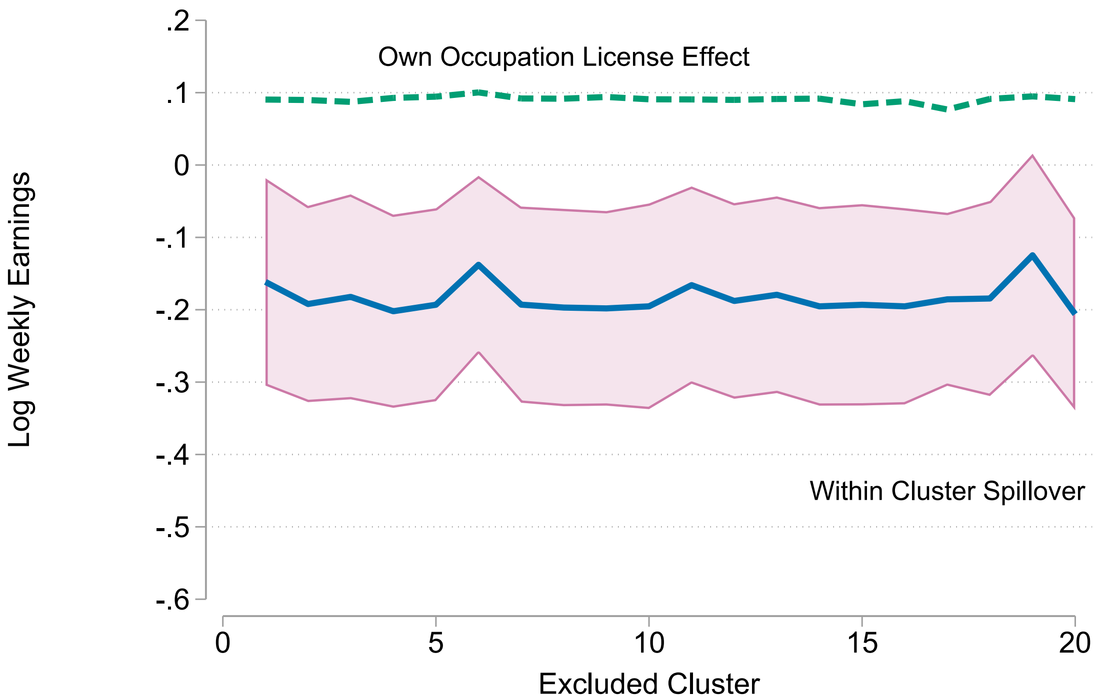

Source: Author's calculations of ACS, O*NET, and CPS licensing data.
Note: Coefficients are generated from the border match design detailed in Equation 7. Standard errors are clustered at the occupation level. 95% confidence intervals in red. Spillover coefficients are based on 100% licensure of an occupation's cluster outside their own occupation.

Figure A3: Coefficients of Log Weekly Earnings by Number of Clusters, by Race/Ethnicity All Occupations, Adding PUMA FE



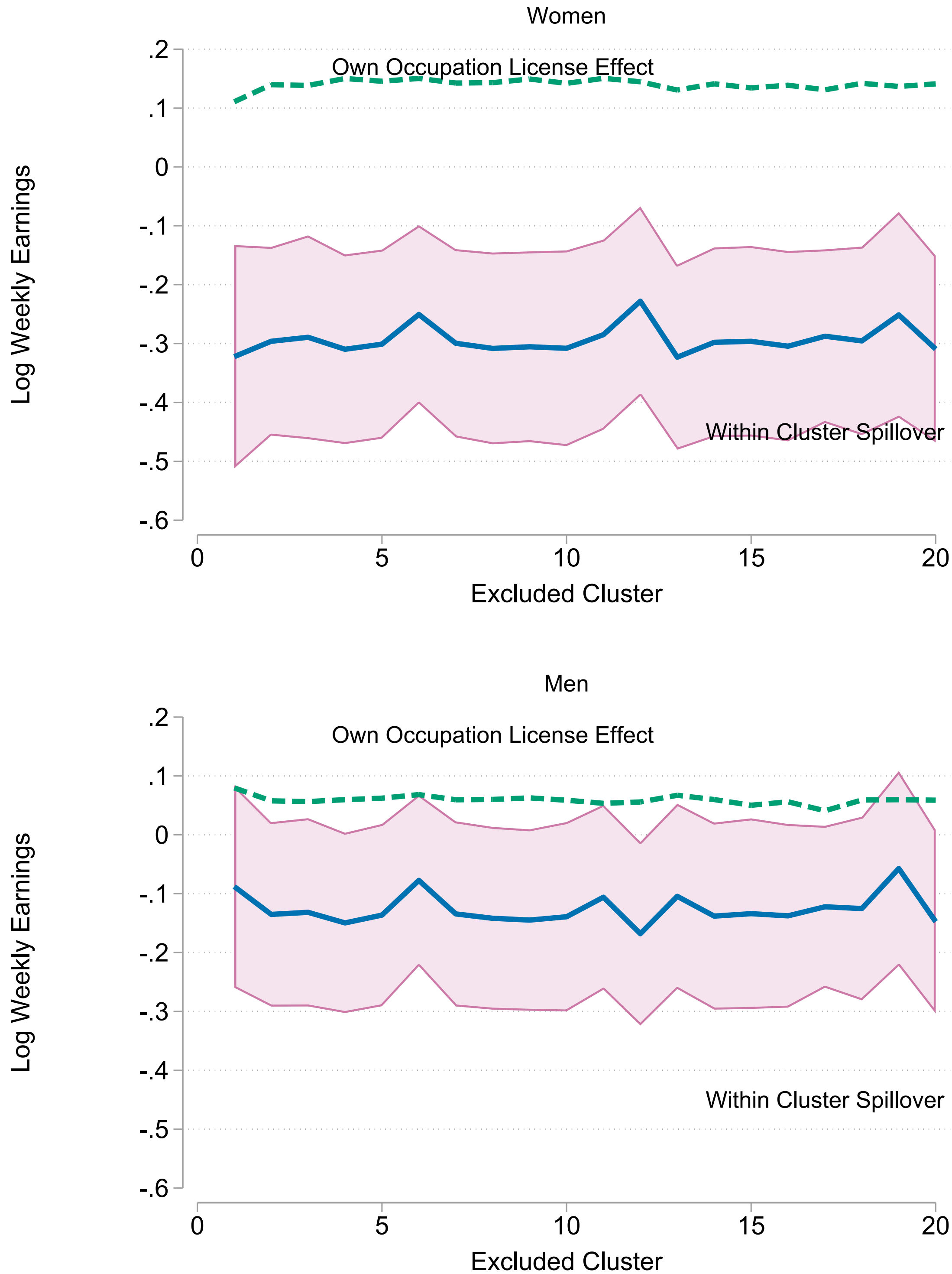

Source: Author's calculations of ACS, O*NET, and CPS licensing data.
Note: Coefficients are generated from the border match design detailed in Equation 7. Standard errors are clustered at the occupation level. 95% confidence intervals in red. Spillover coefficients are based on 100% licensure of an occupation's cluster outside their own occupation.

Figure A4: Earnings Effects, Sequentially Removing Clusters
20 Clusters



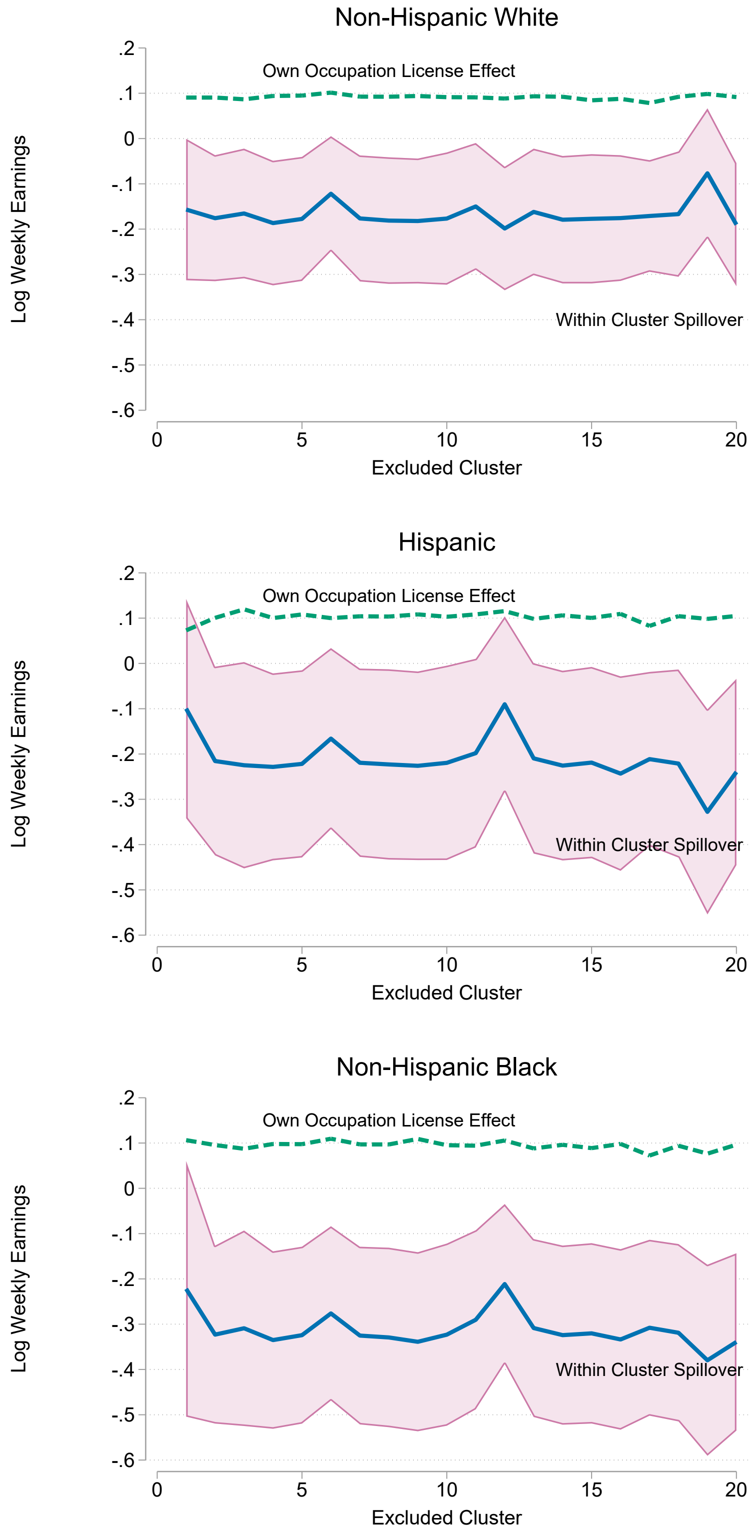

Source: Author's calculations of ACS, O*NET, and CPS licensing data.
Note: Coefficients are generated from the border match design detailed in Equation 7. Standard errors are clustered at the occupation level. 95% confidence intervals in red. Spillover coefficients are based on 100% licensure of an occupation's cluster outside their own occupation for 20 total defined clusters, eliminating one cluster at a time.

Figure A5: Earnings Effects, Sequentially Removing Clusters
By Gender, 20 Clusters



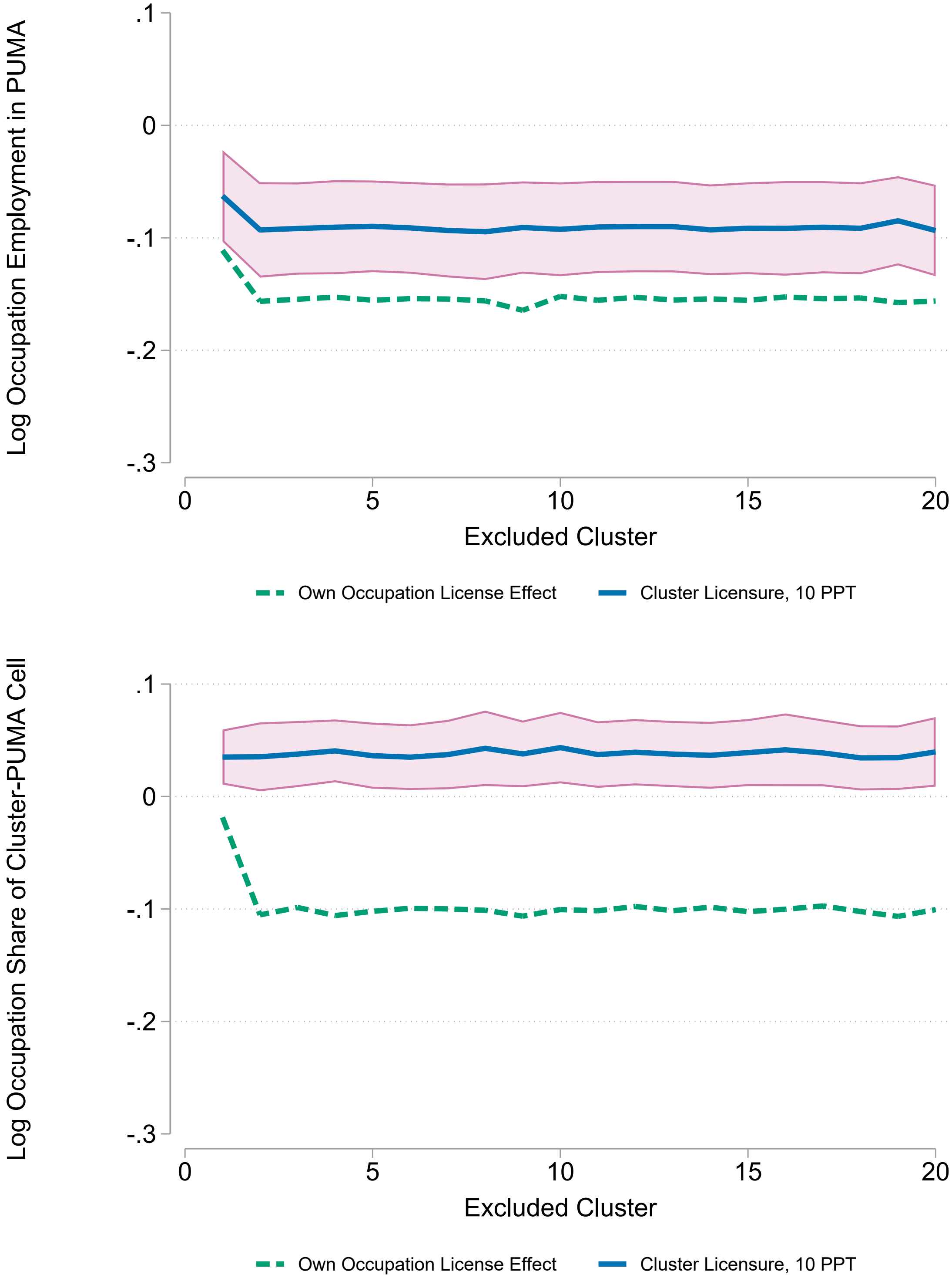

Source: Author's calculations of ACS, O*NET, and CPS licensing data.
Note: Coefficients are generated from the border match design detailed in Equation 7. Standard errors are clustered at the occupation level. 95% confidence intervals in red. Spillover coefficients are based on 100% licensure of an occupation's cluster outside their own occupation for 20 total defined clusters, eliminating one cluster at a time.

Figure A6: Earnings Effects, Sequentially Removing Clusters
By Race/Ethnicity, 20 Clusters



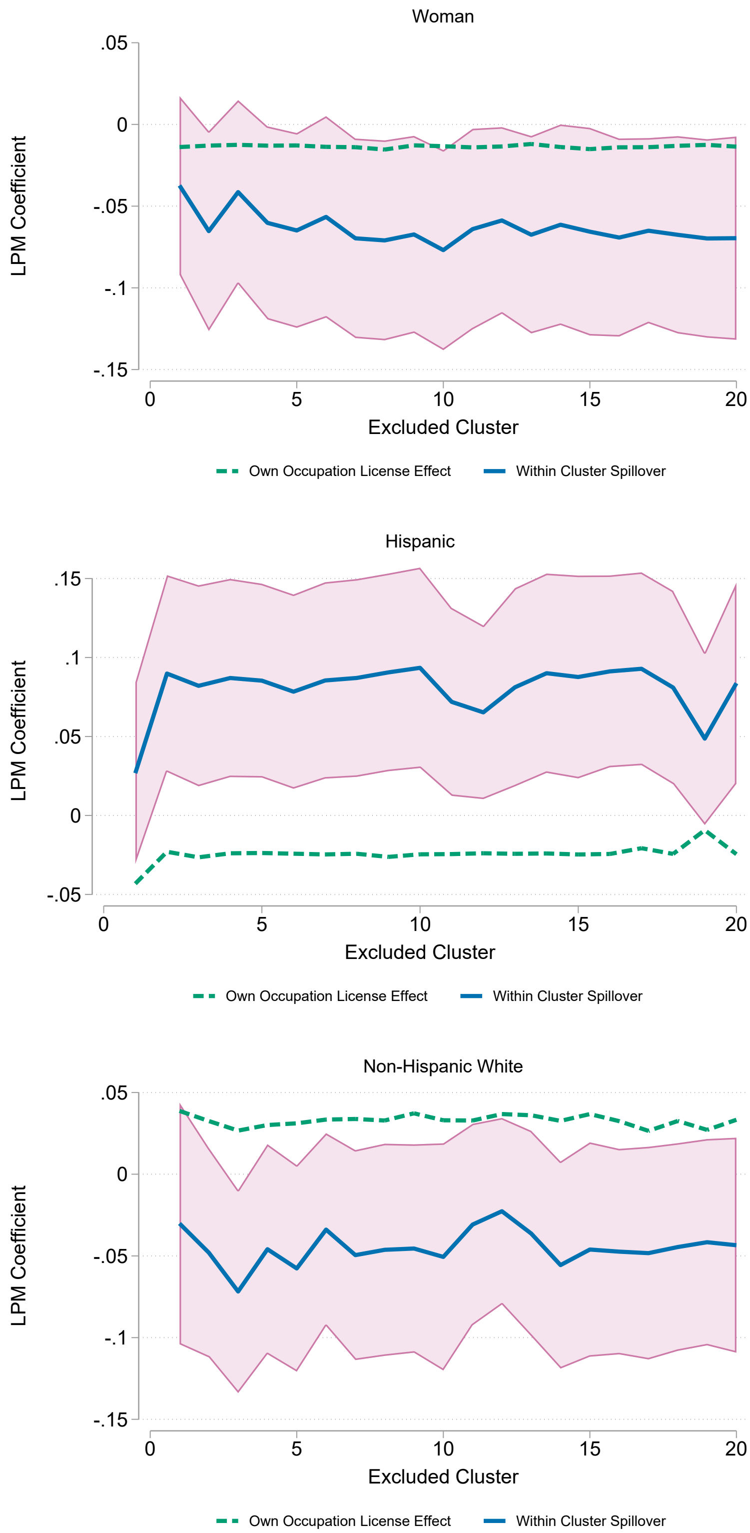

Source: Author's calculations of ACS, O*NET, and CPS licensing data.
Note: Coefficients are generated from the border match design detailed in Equation 7. Standard errors are clustered at the occupation level. 95% confidence intervals in red. Spillover coefficients are based on 100% licensure of an occupation's cluster outside their own occupation for 20 total defined clusters, eliminating one cluster at a time.

Figure A7: Employment Effects, Sequentially Removing Clusters
20 Clusters



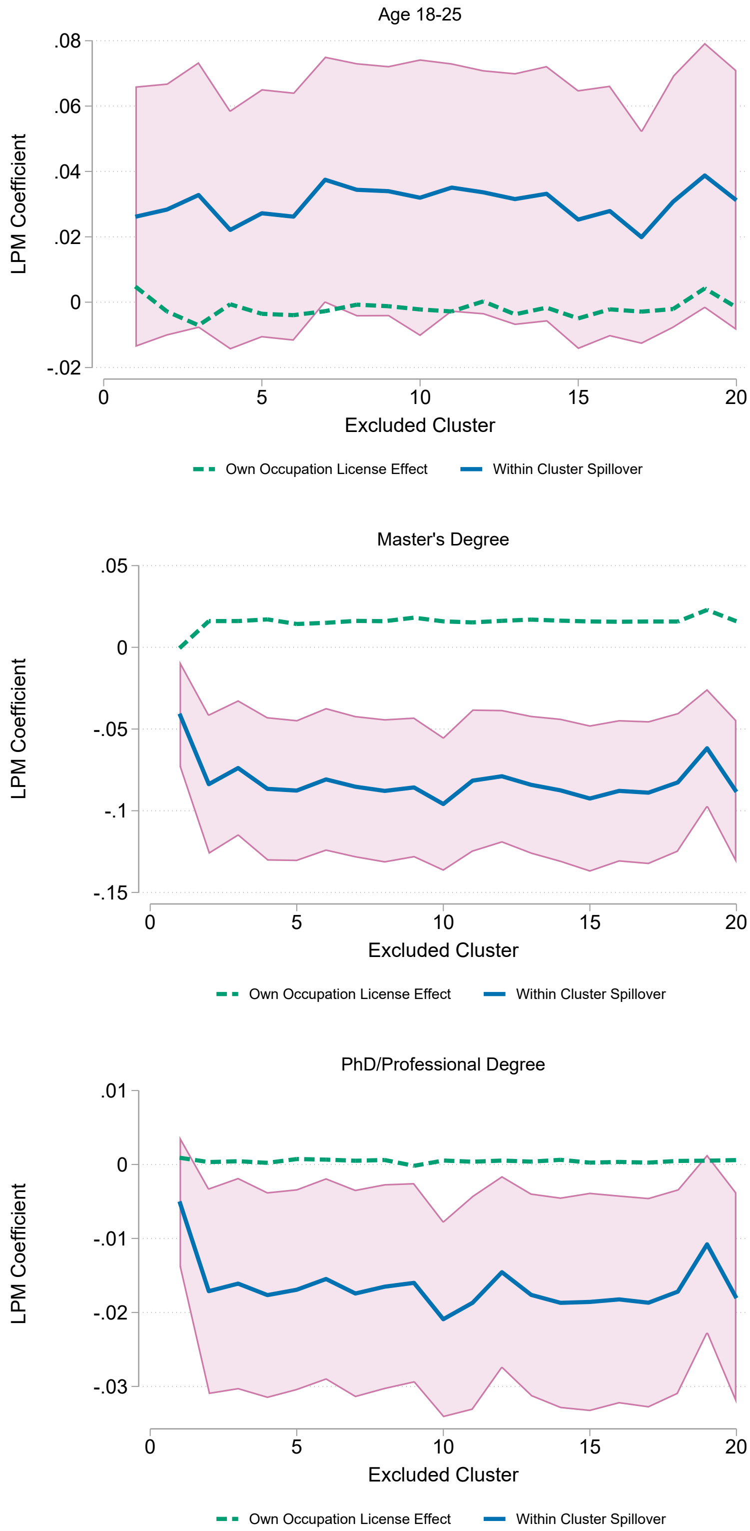

Source: Author's calculations of ACS, O*NET, and CPS licensing data.
Note: Coefficients are generated from the border match design detailed in Equation 7. Standard errors are clustered at the occupation level. 95% confidence intervals in red. Spillover coefficients are based on 100% licensure of an occupation's cluster outside their own occupation for 20 total defined clusters, eliminating one cluster at a time.

Figure A8: Composition Effects, Sequentially Removing Clusters, Sex and Race/Ethnicity 20 Clusters



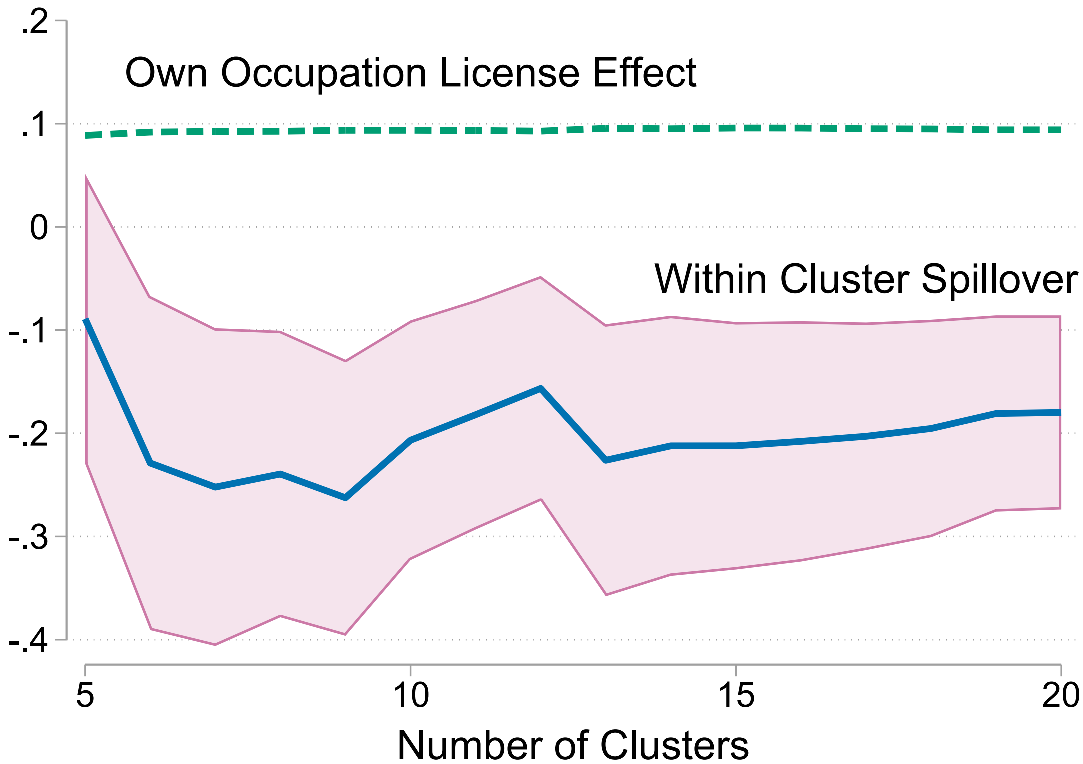

Source: Author's calculations of ACS, O*NET, and CPS licensing data.
Note: Coefficients are generated from the border match design detailed in Equation 7. Standard errors are clustered at the occupation level. 95% confidence intervals in red. Spillover coefficients are based on 100% licensure of an occupation's cluster outside their own occupation for 20 total defined clusters, eliminating one cluster at a time.

Figure A9: 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 7. 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 A10: 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.

Table A1: 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.