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Abstract

Occupational credentials provide an additional—and, at times, alternative—path other than traditional academic degrees for individuals to increase productivity and demonstrate their abilities and qualifications to employers. These credentials take the form of licenses and certifications. Although a critical part of the workforce landscape, the literature on the returns to credentials is inadequate, with prior research having limited causal identification, typically relying on OLS regressions which do not sufficiently control for selection. Using questions that identify credential receipt from the 2015 and 2016 Current Population Surveys, we construct an instrumental variable of local peer influence using the within-labor market credential rate of individuals sharing the same sociodemographic characteristics, while controlling for the same group's average wages and a suite of demographic and geographic controls. We use this instrument in a marginal treatment effects estimator, which allows for estimation of the average treatment effect and determines the direction of selection, and we estimate the effects of credentials on labor market outcomes. We find large, meaningful returns in the form of increased employment, an effect which is concentrated primarily among women. The effect of having a credential on log wages is higher for those in the sub-baccalaureate labor market, suggesting the potential role of occupational credentials as an alternative path to marketable human capital and a signal of skills in the absence of a bachelor's degree.

Keywords: human capital, credentials, certifications, licenses

JEL classifications: J44, J24, J40, J01

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1. Introduction

There has been an unprecedented expansion of the higher education system in the United States over the past three decades, fueled in part by the labor market's demand for workers with education and training beyond a high school diploma. A defining feature of this expansion is the development and proliferation of occupational credentials via non-traditional postsecondary pathways. However, these credentials exhibit significant heterogeneity along several dimensions: in the occupational requirements for specific credentials, in the ways that students choose what credentials to pursue, and in the ways that employers evaluate potential hires based on their possession of these credentials. With such heterogeneity, it remains unclear whether the acquisition of such credentials has a payoff exceeding the efforts and costs for students when they enter the workforce, and whether the magnitude of that payoff varies according to the type of traditional academic degree with which the occupational credential is "paired."

This paper provides causal estimates of the overall employment and wage returns to the two most common types of occupational credentials: licenses and certifications. Licenses are credentials awarded by a governmental licensing agency, typically at the state level, based on predetermined criteria that may include some combination of degree attainment, educational certifications, assessments, apprenticeship programs, or work experience. Examples include cosmetology licenses, teaching licenses, pharmacist licenses, and heating, ventilation, and air conditioning (HVAC) repair licenses. Certifications are credentials typically awarded by a non-governmental certification body to individuals who demonstrate that they have acquired the designated knowledge, skills, and abilities to perform a specific job or task. Examples include information technology certifications (e.g., network support, programming, etc.) and project management professional certifications. One key difference between a certification and a license is that a license conveys a legal authority to work in an occupation, whereas a certification is not lawfully required in order to work in the field of the certification. Over the years, occupational licensing has become a more central feature of the labor market with 26 percent of occupations requiring a license in 2012, up from 17 percent of occupations requiring licenses in 1983 (Redbird, 2017). Most certifications and licenses – particularly those aimed at workers in the sub-baccalaureate labor market – eschew traditional liberal arts coursework and seat time in favor of the development and demonstration of occupation-specific competencies.

The goal of our study is to assess whether occupational credentials accrue distinct labor market benefits in the form of higher employment rates and wages, and whether these returns vary depending upon the type of traditional academic degree with which it is paired. We hypothesize that holding a credential will yield strong labor market returns as a signal of human capital and potential productivity. We further expect the returns to be higher for licenses than for certifications because licenses impose a form of "occupational closure" where certain tasks in the economy can only be performed legally by a select set of workers (Weeden, 2002). This closure allows for tighter control over supply and in turn creates a form of monopolization of certain parts of the economy that distinctly benefits those in possession of the license when demand for licensed labor is high.

Despite the important role credentials play in sorting workers into occupations, the research base on the economics of credentials is still in its infancy. Historically, occupational credential attainment has been imprecisely and/or inconsistently measured in large-scale, nationally-representative surveys used to study education and labor market outcomes. Hence, there are few national-level studies that examine the outcomes of occupational license holders across all segments of the economy. We aim to bolster this nascent body of research by analyzing data from the 2015 and 2016 Current Population Surveys (CPS), one of the first national surveys to include questions that permit the identification of sample members with certifications and licenses. In addition to improved data, we employ the method of marginal treatment effects (MTE) with instrumental variables, a generalized Roy model, which permits (with some assumptions) the identification of a *continuum* of treatment effects, including the average expected treatment effect and the average treatment effect for the untreated population, key for structuring policy incentives. This exercise is similar to Carneiro, Heckman, and Vytlacil (2011), who use MTE to estimate the returns to education.

Our study makes three key contributions to the literature. First, in order to examine the relationship between occupational credentials and labor market outcomes, we develop a novel "local peer influence" instrumental variable: a leave-one-out estimator of the proportion of individuals in the same local demographic group (gender by race by education level) in the same Core-Based Statistical Area (CBSA) that have an occupational credential, all while controlling for gender, race, and education level of the individual, the same local demographic group's average wage, and local market labor force participation and unemployment rates as independent factors. We validate this instrument by estimating the return to an associate degree using the same type of instrument, and contextualizing the point estimate with prior research. Second, we leverage this instrument to produce causal estimates of the effect of licenses and certifications on employment and earnings, contributing to the literature that has previously identified these premia from cross-sectional and fixed effects regressions. Third, we document substantial heterogeneity in the returns to occupational credentials along two dimensions: bachelor's degree attainment and gender.

In what follows, we first review past research on the labor market returns to occupational credentials and develop specific hypotheses. Next, we outline our empirical model and discuss how we use the CPS to estimate it. We then present our results and conclude with a summary of our findings.

2. Background

2.1 Past Research on Occupational Licenses

Despite their growing popularity, social science's understanding is still evolving regarding the role that occupational credentials play in preparing students for the labor force, in the production of human capital more broadly, and in how employers interpret these credentials as evidence of competencies when making hiring and salary decisions. At the federal level, research efforts have been led in part by the Interagency Working Group on Expanded Measures of Enrollment and Attainment (GEMEnA), a federally-commissioned group tasked with developing and validating measures of the participation in and credentialing of education and training for work, including metrics that measure the attainment of occupational credentials. Prior to GEMEnA, federal surveys had disparate approaches for asking sample members about occupational credentials, with some asking about them in survey modules focused on educational attainment and school enrollment, with others asking about them in survey modules focused on job training. Without standardized, systematic metrics in federal surveys, it was not possible to reliably study credentials across occupations at the national level. By creating these new "gold standard" metrics, GEMEnA has laid the foundation for social scientists to embark on new research in the areas of educational attainment and workforce development.

Pre-GEMEnA attempts at estimating the labor market returns to licenses and certifications yielded mixed results. Kleiner and colleagues analyzed an array of cross-sectional nationally representative surveys and found that wages were between 10 and 18% higher among those with licenses when compared to those without (Kleiner and Kruger, 2010; Kleiner and Kruger, 2013;

Kleiner and Vorotnikov, 2017). In these surveys, the estimated returns to certifications were substantially smaller (Kleiner and Kruger, 2013; Kleiner and Vorotnikov, 2017). In contrast, however, research using the Education Longitudinal Study of 2002, which tracked a nationally representative cohort of high school graduates from the class of 2004, identified an earnings premium of between 14% and 25% percent from holding a certification among young adults (Albert, 2017).

Lacking data that included direct measures of occupational credentials, Redbird (2017) pooled data from the 1983-2012 Current Population Survey (prior to its implementation of GEMEnA's measures in 2015) and used state laws regarding licensure requirements for specific occupations to determine whether or not workers in states that required licenses for their occupations earned more than their counterparts holding the same occupation in states that did not require licenses. She found no association between state licensure laws and wages. The treatment effect identified under these conditions is a very specific one: the returns to having a license because the state requires one. There may, however, be strong returns to obtaining a license or certification in a state where they are not required, as the receipt of the credential may serve to distinguish the human capital of credential holders in hiring or promoting processes in those states.

One of the first surveys to incorporate GEMEnA's measures was the 2012 Survey of Income and Program Participation (SIPP), which is a nationally representative household-based survey collected by the U.S. Census Bureau. Once these new metrics were added to the SIPP, it was estimated that 21.6 percent of adults in the country held a currently active certification or license, with rates of receipt higher among those with more advanced traditional academic degrees such (such as bachelor's degrees) than those with high school diplomas and associate degrees (Ewert and Kominski, 2014). Using this data, Gittleman et al. (2018) found that adults with licenses were more likely to be employed, and if employed, had 7% higher wages than their peers without licenses. Gittleman and Kleiner (2016) used the National Longitudinal Study of Youth to identify individuals who switch into or out of occupations that require licenses in their state of residence, and from that, estimate a fixed effects model of the return to switching into a license-required occupation. They found the wage growth from such a switch to be between 2% and 7%. Finally, Ingram (2019) used data from the CPS, which also included the occupational credential questions per the guidance of GEMEnA, to estimate a propensity score model of the licensure earnings premium. He additionally leveraged state variation in licensure rates to estimate a model using metropolitan statistical areas (MSAs) spanning state borders, estimating wage returns of between 4% and 8%.

While informative, these studies have a number of limitations. The analyses conducted by Kleiner and his colleagues used cross-sectional data with low response rates, and so had a limited ability to account for selection and may be affected by non-response bias. Redbird (2017) and Albert's (2017) analyses used data from nationally-representative surveys with larger samples and higher response rates but were conducted prior to the development of the GEMEnA measures, and in the case of Redbird's (2017) study, direct measures of licensure were not available, and were thus inferred. Gittleman et al.'s (2018) analysis benefits from the strong survey properties of the SIPP and the inclusion of the GEMEnA measures, but used cross-sectional OLS regressions which did not control for selection or omitted variable bias. Consequently, their estimated earnings benefits likely reflect some dimensions of positive selection into occupational credential programs. Gittleman and Kleiner (2016) meanwhile use the NLSY and are able to control for time-invariant omitted variable bias through individual fixed effects, but, like Redbird (2017), do not observe actual licensure status (instead inferring it from their occupation and state, and the laws for that state and occupation). As a consequence, they were unable to identify returns to licenses in states that do not require them.

Lastly, Ingram's (2019) propensity score matching analysis of the CPS was able to take advantage of a large nationally-representative survey with high response rates and the inclusion of the GEMEnA measures. However, matching estimators are only able to match based on observed characteristics, whereas it is likely that there is a difference between those with credentials and those without credentials based on unobserved ability and motivation measures. Additionally, propensity score estimators require a common support, and thus constrain estimation to narrow and perhaps unique segments of the sample where there are available matches on observed characteristics. This leads to limited generalizability to the broader population. Our paper offers an alternative strategy to estimating the causal returns that circumvents these limitations.

In our analysis, we build on this growing body of research by analyzing data from the 2015 and 2016 CPS which includes a large nationally representative sample, high response rates, and employ the occupational credential questions per the guidance of GEMEnA. To attenuate potential bias owing to selection and omitted variables, we use a local peer influence instrument via the within-CBSA credential rates of local individuals sharing the same sociodemographic characteristics as instruments, and we include the inverse mills ratios in the second stage of Heckman regressions that predict wages. In using the first two years in which the GEMEnA measures were included on the CPS and incorporating instrumental variables to attenuate possible selection bias in estimating the effects of occupational credentials on labor market outcomes, our study improves upon past research that attempts to understand how the provision of licenses and certifications can directly benefit workers.

Of course, even if occupational credentials have a positive return for those who attain them, there may be adverse effects on the economy. Kleiner and Soltas (2018) found that licensing serves as a bureaucratic hurdle to finding a job and leads to lower overall employment (despite higher wages observed for those with licenses). In a recent working paper, Carollo (2020) notes that these disemployment effects are concentrated among occupations that pose minimal risk of harm to the public upon worker failure (unlike, for example, healthcare and construction jobs). However, the aggregate effects of state-level decisions to license occupations are beyond the scope of this study, which limits attention to the benefits that accrue directly to individual credential holders.

2.2 Contingent Effects of Traditional Academic Degrees

A distinctive quality of licenses and certifications is that they can serve as "capstones" on top of traditional academic degrees, which in turn collectively signal occupation-specific qualifications to prospective employers. The value of these signals likely varies depending on the level of education of the traditional academic degree, which are central markers of human capital. As mentioned earlier, licenses and certifications are less prevalent among those in the sub-baccalaureate labor market than among those with a bachelor's degree (Ewert and Kominski, 2014). Additionally, bachelor's degrees convey a more comprehensive set of skills and capabilities than associate degrees or high school diplomas. Therefore, we hypothesize that occupational credentials serve to differentiate high-quality sub-baccalaureate job applicants moreso than for those with bachelor's degrees, which would result in potentially larger returns to these credentials.

To illustrate, consider two hypothetical recent college graduates. The first has an associate degree in business administration and is considering a job as an administrative assistant in a marketing consulting firm. While there are no licenses required to be an administrative assistant, the job applicant might opt to acquire a computing certification (e.g., a Microsoft certification or a Cisco certification) to enhance their hiring prospects. The second has a bachelor's degree in business administration and is seeking a job as a portfolio manager at the same marketing consulting firm. Similar to the first applicant, this second applicant has acquired a computing certification for an entry-level job they held while working their way through college. In the situation of the associate degree holder, the certification may serve to differentiate the applicant from the rest of the pool of low-skill workers aiming for the administrative assistant position. In the situation of the bachelor's degree holder seeking a portfolio manager position, the certification is potentially less relevant to the employer than their bachelor's degree. Therefore, the returns to the associate degree holder's certification should be higher than the returns to the bachelor's degree holder's certification, holding industry/occupation and education constant.

2.3 Contingent Effects of Gender

We additionally explore heterogeneity in returns to occupational credentials by gender. Educational attainment has been increasing among women, in tandem with a college earnings premium that is larger for women than for men (DiPrete and Buchmann, 2006). Despite this growth, sizeable wage and employment gaps by gender remain (e.g., Goldin and Rouse, 2000; Blau and Kahn, 2017). In particular, women face substantial discrimination in the hiring process in part because employers believe female applicants are more committed to family than their jobs (Blau and Kahn, 2017) and in part because employers believe female applicants are less capable to perform the tasks required for the job (Coffman et al., 2018). It is possible that occupational credentials on women's resumes could attenuate these sources of discrimination by signaling commitment to career and enhanced workplace competencies. The evidence to date suggests this might be the case. For example, Blair and Chung's (2017) analysis of the Survey of Income and Program Participation documents the potential of license acquisition by women to reduce gender wage gaps. Similarly, Law and Marks (2009) find that historically, occupational licensure led to increased employment in skilled and licensed fields for female workers. Therefore, we hypothesize that occupational credentials will bolster the labor market prospects of women more than for men.

3. Methods

The central objective of our analysis is to estimate the returns to occupational licenses and certifications. We examine two outcomes: the probability of being employed conditional on being in the labor force, and log hourly wages conditional on being employed.

3.1 The Instrumental Variable

Prior evaluations of the returns to credentials have relied on regressing labor market outcomes on credential status as well as a broad set of individual controls, including education level and in some cases, individual fixed effects. However, these approaches may be biased, for all of the same reasons a similar regression of returns to education are known to be biased. These reasons include the omitted variable bias of not observing and thus failing to control for factors that select individuals into license programs (such as ability, interests, career goals, etc.); bias from selection on heterogeneity in the anticipated returns to license or credit constraints; and so forth. This necessitates an approach that can tease out the true returns to credentials either across the distribution (such as expressed through Marginal Treatment Effects, or MTE) or some average of the population, such as for the entire group (Average Treatment Effect, or ATE), for those that get credentials (Average Treatment Effect on the Treated, or ATT), and for those that do not get credentials (Average Treatment Effect on the Untreated, or ATU), or the treatment effect for those affected by the instrument (the Local Average Treatment Effect, or LATE).

An instrumental variable method is one approach we can use to estimate these parameters. As discussed, the existing literature has not, to date, incorporated an instrumental variable when estimating the returns to occupational credentials. However, the literature on returns to formal education, such as bachelor's degree attainment, have used instrumental variables extensively. Some commonly used instrumental variables include the distance between home and colleges (Card, 1995; Doyle and Skinner, 2016), changes in tuition costs and financial aid availability (Velez et al., 2019), and changes in mandatory schooling thresholds (van Huellen and Qin, 2019; Balestra and Backes-Gellner, 2017; Oreopolous, 2006); see Card 2001 for a review of this literature. For occupational credentials, however, we cannot use these previously used instruments. Credentials can be acquired in several unobserved locations, including some through online learning, rendering geographic distances less relevant. Tuition costs for these programs vary tremendously across states and over time, but there is not a readily available cost database for the universe of these programs, nor documentation for what credential each person has in our data, let alone where they acquired it. Additionally, there are often no mandatory age requirements for credentials, and no requirements of necessary training for groups (that is, that individuals must attend training classes, whether or not they want to work in that area).

Lacking guidance of previously-used and well-established instrumental variables from the returns-to-schooling literature that could be applied to returns to credentials, we introduce an instrument that is "local peer influence" based, working on the assumption that peer groups that have higher rates of credentialing may increase the propensity of individuals in that peer group to pursue and acquire credentials. The use of this instrument is motivated by research which shows that net of sociodemographic and academic characteristics, peer groups influence academic achievement (Calvó-Armengol, 2009; Hanushek et al., 2003) and college enrollment (Fletcher, 2012; 2015). In our study, local peer groups are defined as the people that live in the same Core-Based Statistical Area (CBSA) and are the same gender, race/ethnicity (American Indian, Asian, Black, Hispanic, White, or other, where all racial groupings are for the non-Hispanic), educational attainment, and are within the age band of five years younger to 15 years older.[1] Our sample has 358 unique CBSAs, with several local peer groups within each CBSA by race/ethnicity, gender, educational attainment, and age). The average number of observations in the peer group is around 240 with a median of 144 observations. To illustrate the operationalization of our instrument, take for example, a 44-year-old Hispanic man in the Columbus, Ohio CBSA with an associate degree. For this individual, we calculate a leave-one-out estimator of the proportion of Hispanic men between 39 and 59 years old in Columbus with an associate degree that have a license.

3.2 Outcome Model Specification

Equations 1 and 2 present the regression specifications we use as our second-stage regressions for the two outcomes, the probability of being employed (emp_{ijst}) conditional on being in the labor force and log hourly wages ($lnwage_{ijst}$) conditional on being employed.

$$emp_{ijst} = \alpha + \beta Cred_i + X_i\gamma + \rho_1 PeerEarn_{ij} + \rho_2 LocalEarn_{ij} + \phi unemp_{jt} + \lambda lfpart_{jt} + \psi_s + \theta_t + \varepsilon_{ijst} \quad (1)$$

$$lnwage_{ijst} = \alpha + \beta Cred_i + X_i\gamma + \rho_1 PeerEarn_{ij} + \rho_2 LocalEarn_{ij} + \lambda_1 potexp_i + \lambda_2 potexp_i^2 + \phi_1 unemp_{jt} + \phi_2 lfpart_{jt} + \psi_s + \theta_t + \kappa IMR_{ijst} + \varepsilon_{ijst} \quad (2)$$

[1] We use the non-symmetric band for age on the assumption that most individuals look to their peers for signals of appropriate behaviors, with greater weight toward those older than themselves who are further along in their schooling and careers. We tested several other age bracket options: a narrow band (two years younger to five years older), a broad band (10 years younger to 30 years older), and no age restriction. We selected the age band we did as it minimized the mean squared predicted error of our model (using the first stage regression including other covariates).

The primary regressor of interest is $Cred_i$, an indicator for holding a credential (separately, licenses or certifications). In addition, employment and earnings are functions of individual characteristics including educational attainment, race, age, and gender (X_i). The outcomes are also functions of local labor market conditions. Therefore, we control for the county's unemployment rate ($unemp_{jt}$), the labor force participation rate ($lfpart_{jt}$), and include state fixed effects (ψ_s). It is important to control for these measures of labor market conditions, as these are correlated with decisions to credential and the outcomes, as well as the instrumental variables themselves (Cameron and Heckman, 1998, 2001). We also control for time fixed effects (θ_t), and for log wage, we include a quadratic in potential labor market experience ($potexp_i$) and the inverse mills ratio (IMR_{ijst}) so as to adjust for the selection into being employed.[2] As described above, we instrument credential status using the local peer influence instrument, included in the first stage.

We may still worry that even after controlling for this array of potential confounds, there remains a direct impact of a higher-credentialed local peer group on an individual's employment outcomes, which would violate the exclusion restriction of the instrument: a group motivated enough to pursue credentialing may be strong in other ways that improves labor outcomes, even after controlling for the direct differences in group earnings through X_i. To address this concern, we include as additional control variables a leave-one-out estimator for the local peer group's average earnings (allowing for zeros for non-employment) and the across-demographic local average earnings ($PeerEarn_{ij}$ and $LocalEarn_{ij}$, respectively). We argue that these control for remaining direct impacts of the peer group on the outcomes as well as the strength of the local labor market, such that any residual impact of the local peer group credential rate on an individual's own credentialing probability is the remaining pathway in which the local peer group can impact an individual's labor outcomes, after controlling for all other variables.

For smaller regions and smaller peer groups, we adjust the definition of the instrument ($PeerCred_{ij}$) and peer earnings measure ($PeerEarn_{ij}$) to use the local rate aggregated *across* demographic groups, rather than within, still limited to the CBSA. We perform this adjustment when the sample size on which to estimate the local peer credential rate is fewer than 30

[2] For the log wage regression, we use a Heckman selection mechanism by including the inverse mills ratio (IMR) for the probability of employment. For the IMR, our excluded instruments are the triple interactions among gender, marital status, and having dependents. We hypothesize that there are differences in employment along the intersections of these demographic variables that are not fully explained by the subgroups alone.

observations across the two years of data, which occurs for 13.7 percent of our observations. Additionally, we note that in the CPS, the CBSA is the metropolitan statistical area (MSA) for areas connected to an MSA; for an individual living outside any MSA, their CBSA is functionally a state identifier that excludes all MSAs in the state.

The first stage equations that predict credential status models credential status as a function of all other covariates in equations 1 and 2 (for each outcome respectively), as well as the local peer influence measure, our instrumental variable, using a probit model. For a validation check of our instrument, as well as an internal comparison of the returns to licenses and the returns to education, we construct the parallel local peer influence instrument for having an associate degree among those with less than a bachelor's degree, and estimate identical models examining the returns to an associate degree. We are thus able to compare the estimated returns to an associate degree using our instrument to the literature on the returns to associate degrees; as detailed later, it compares very favorably, supporting the use of our instrument for credentials.

3.3 MTE Modeling Framework

We use the instruments in the MTE estimation framework summarized in Cornelissen et al. (2016) (see also Carneiro, Heckman, and Vytlacil, 2011). We apply the parametric Roy model of MTE, which allows us to estimate additional parameters other than LATE, by leveraging the continuous nature of our instrumental variable (IV). Intuitively, the MTE estimates several LATEs along the entire distribution of the continuous IV. This allows for repeated estimates of a LATE at different levels of what the literature calls the (unobserved) distaste for treatment. These marginal treatment effects can then be aggregated up to estimate, for example, the ATE by adjusting to the sample population level given the distribution of the IV in the sample. This represents a major advantage of the MTE estimator: LATE is not likely to be highly policy-relevant in our case, given our instrument, as we care about the returns not only for individuals that would be motivated to pursue a credential only with sufficient peer support, but rather for the population more generally. Using the MTE model, we are able to estimate the ATE, ATT, ATU, the LATE of the returns, and map out the returns across the MTE curve as a function of the distaste for treatment. As described in Cornelissen et al. (2016), the marginal treatment effect estimator is given by

$$MTE(X_i = x, U_{Di} = p) = \frac{\partial E(Y_i | X_i = x, P(Z_i) = p\ )}{\partial p} \tag{3}$$

U_{Di} is the percentile of the unobserved distaste for treatment, Z_i is our continuous instrumental variable, and p is the probability of receiving a credential. We present the MTE curves as a function of U_{Di} for the average observable characteristics X_i. The estimates are weighted averages of the MTE across certain populations (e.g., across the treated group for the ATT).

3.4 Decomposition Methodology

We are additionally interested in decomposing the net returns to wages, allowing for the effect to be a function of not only the returns to wages conditional on working, but also the returns driven by changes in the likelihood of employment. Letting *w* be hourly wages and *emp* be the employment status, and restricting all to individuals within the labor force, we note that by the law of total probability and the fact that non-workers have zero wages,

$$E[w|X] = E[w|X, emp = 1] \Pr(emp = 1|X) \tag{4}$$

The overall difference in wages between those that have a credential ($Cred = 1$) versus those that do not ($Cred = 0$) can be decomposed as

$$\begin{aligned} & E[w|X, Cred = 1] - E[w|X, Cred = 0] \\ & \quad = E[w|X, emp = 1, Cred = 1] \Pr(emp = 1|X, Cred = 1) \\ & \quad - E[w|X, emp = 1, Cred = 0] \Pr(emp = 1|X, Cred = 0) \\ & = \beta_W \Pr(emp = 1|X, Cred = 1) + \beta_E E[w|X, emp = 1, Cred = 0] \end{aligned} \tag{5}$$

Where

$$\begin{aligned} \beta_W &= E[w|X, emp = 1, Cred = 1] - E[w|X, emp = 1, Cred = 1] \\ \beta_E &= \Pr(emp = 1|X, Cred = 1) - \Pr(emp = 1|X, Cred = 0) \end{aligned} \tag{6}$$

The total returns are the sum of two elements: β_W, the earning returns conditional on working (the typically-estimated return), or the intensive margin of the effect; and β_E, the earning returns to employment given being in the labor force (e.g., that credential status changes the likelihood of being employed, and thus receiving labor wages), or the extensive margin of the effect. We estimate each of the four elements of equation 5 to construct the decomposition.

Given the data-driven construction of the instruments, analysis being conducted across multiple stages, use of IMR within the MTE framework, and the decomposition being a function of several parameters from separate regressions with different samples, we bootstrap all of the standard errors. We block-bootstrap at the CBSA level with 500 bootstraps to account for within-labor market intraclass correlation that would otherwise bias the standard errors.

4. Data

For our analysis, we pool the 2015 and 2016 Current Population Surveys (CPS), which contained a set of questions used to determine occupational credentialing developed by GEMEnA. We limit the sample to individuals between ages 18 and 65 – the working population – that that are not enrolled in school.[3] Tables 1 and 2 present the characteristics and distribution of the overall sample, stratified by educational attainment and credential status.

In the CPS, sample members are first asked: “Do you have a currently active professional certification or a state or industry license? Do not include business licenses, such as a liquor license or vending license.” If they respond yes, they are then asked: “Were any of your certifications or licenses issued by the federal, state, or local government?” If they respond no, they are considered to only have a certification. If they respond yes, they are considered to have a license. Receiving a license and receiving a certification are not mutually exclusive, and hence there are four ways to classify workers: those with a license but without a certification, those with a certification but without a license, those with both a license and certification, and those with neither. Given the wording of the questions, we cannot identify all four groups separately; specifically, we cannot identify those with licenses but no certifications separately from those with licenses and certifications. We also cannot determine if an individual holds multiple licenses or multiple certifications. As the MTE framework allows only one endogenous variable, we separately estimate (a) the returns to licenses compared to no licenses and no certifications (Column 2 versus column 3 in Tables 1 and 2) as well as (b) the returns to certifications with no licenses to those with no licenses and no certifications (Column 1 versus column 3 in Tables 1 and 2).

Tables 1 and 2 also present the demographic composition of each credential group using the characteristics identifiable in the CPS: gender (male, female), marital status (married, single), race/ethnicity (White, Black, Asian, Hispanic, American Indian), birth cohort (millennial, generation X, baby boomer), and formal educational attainment (less than high school, high school graduate, associate degree, bachelor’s degree, graduate degree). Birth cohorts are defined as follows: millennials were born between 1981 and 1997, generation X’ers were born between 1964 and 1980, and baby boomers were born between 1951 and 1963 (truncated as we only consider individuals through age 65).

[3] We do not limit age when constructing the instrumental variables, so as to have a measure of the degree to which older peers have credentials among those older than age 50.

Table 1: Sample Characteristics, Sub-Baccalaureate

	Certification-holders	License-holders	Non-credential holders	All
Instrumental variables				
Local peer group mean earnings	11.746	11.193	10.220	10.383
	(3.929)	(3.755)	(3.808)	(3.823)
Local group mean earnings	8.639	8.570	8.521	8.530
	(1.181)	(1.155)	(1.152)	(1.153)
Covariates				
Local unemployment rate	0.050	0.050	0.051	0.050
	(0.014)	(0.012)	(0.013)	(0.013)
Local labor force participation rate	0.832	0.832	0.827	0.828
	(0.055)	(0.055)	(0.055)	(0.055)
Potential experience	25.162	26.130	26.484	26.410
	(12.316)	(12.334)	(13.794)	(13.577)
Male	0.593	0.512	0.495	0.499
	(0.491)	(0.500)	(0.500)	(0.500)
Married	0.571	0.589	0.502	0.515
	(0.495)	(0.492)	(0.500)	(0.500)
Any dependents	0.380	0.377	0.311	0.321
	(0.485)	(0.485)	(0.463)	(0.467)
Age: millennial	0.299	0.271	0.312	0.306
	(0.458)	(0.445)	(0.463)	(0.461)
Age: Gen-X	0.413	0.413	0.350	0.360
	(0.492)	(0.492)	(0.477)	(0.480)
Race/Ethnicity: Black	0.107	0.107	0.125	0.122
	(0.310)	(0.309)	(0.330)	(0.327)
Race/Ethnicity: Asian	0.029	0.032	0.042	0.040
	(0.167)	(0.176)	(0.200)	(0.197)
Race/Ethnicity: Hispanic	0.118	0.104	0.184	0.172
	(0.323)	(0.305)	(0.388)	(0.377)
Race/Ethnicity: American Indian	0.008	0.012	0.015	0.014
	(0.087)	(0.109)	(0.120)	(0.118)
Race/Ethnicity: Other	0.015	0.014	0.014	0.014
	(0.123)	(0.118)	(0.117)	(0.117)
Education: HS grad.	0.338	0.343	0.467	0.448
	(0.473)	(0.475)	(0.499)	(0.497)
Education: Some college	0.318	0.291	0.244	0.252
	(0.466)	(0.454)	(0.430)	(0.434)
Education: AA vocation	0.150	0.164	0.051	0.069
	(0.357)	(0.370)	(0.221)	(0.253)
Education: AA academic	0.143	0.151	0.075	0.087
	(0.350)	(0.358)	(0.264)	(0.282)
N	5,863	40,689	250,618	297,170
Percent	2.00%	13.70%	84.30%	100%

Note: Standard deviations in parentheses.

Table 2: Sample Characteristics, Bachelor's Degree or More

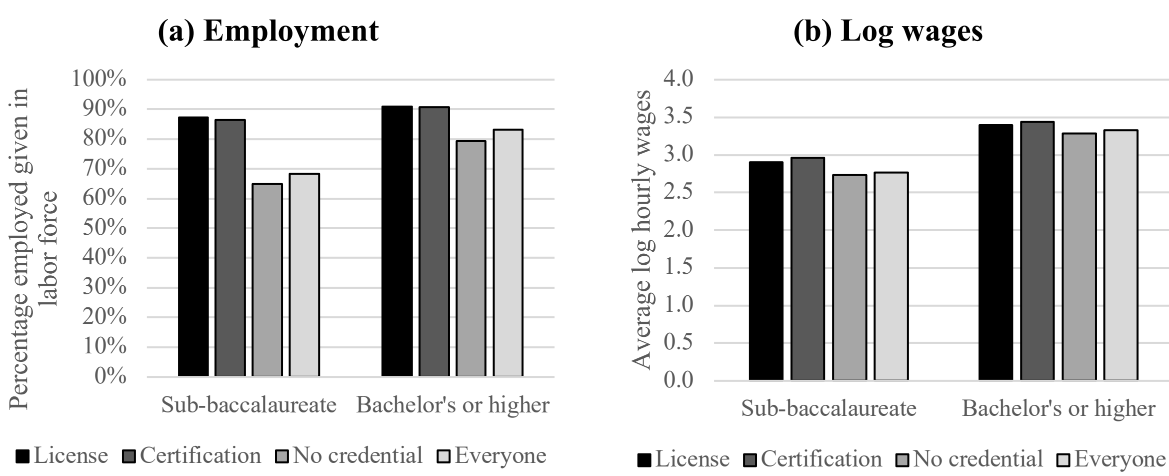
	Certification-holders	License-holders	Non-credential holders	All
Instrumental variables				
Local peer group mean earnings	23.887	22.261	23.190	22.926
	(6.748)	(6.402)	(6.699)	(6.626)
Local group mean earnings	21.480	20.721	21.355	21.163
	(3.432)	(3.403)	(3.515)	(3.491)
Covariates				
Local unemployment rate	0.048	0.049	0.049	0.049
	(0.011)	(0.011)	(0.011)	(0.011)
Local labor force participation rate	0.842	0.838	0.838	0.838
	(0.051)	(0.053)	(0.051)	(0.052)
Potential experience	22.708	23.136	22.088	22.435
	(11.145)	(11.548)	(12.294)	(12.038)
Male	0.522	0.397	0.484	0.458
	(0.500)	(0.489)	(0.500)	(0.498)
Married	0.673	0.698	0.625	0.649
	(0.469)	(0.459)	(0.484)	(0.477)
Any dependents	0.421	0.421	0.360	0.381
	(0.494)	(0.494)	(0.480)	(0.486)
Age: millennial	0.244	0.240	0.301	0.280
	(0.430)	(0.427)	(0.459)	(0.449)
Age: Gen-X	0.459	0.433	0.396	0.410
	(0.498)	(0.496)	(0.489)	(0.492)
Race/Ethnicity: Black	0.063	0.066	0.074	0.071
	(0.243)	(0.249)	(0.261)	(0.257)
Race/Ethnicity: Asian	0.090	0.058	0.103	0.088
	(0.287)	(0.235)	(0.303)	(0.284)
Race/Ethnicity: Hispanic	0.060	0.056	0.070	0.065
	(0.238)	(0.230)	(0.255)	(0.247)
Race/Ethnicity: American Indian	0.004	0.005	0.005	0.005
	(0.061)	(0.073)	(0.068)	(0.069)
Race/Ethnicity: Other	0.013	0.011	0.011	0.011
	(0.111)	(0.105)	(0.104)	(0.104)
Education: Masters	0.315	0.324	0.227	0.260
	(0.464)	(0.468)	(0.419)	(0.439)
Education: Professional degree	0.040	0.101	0.017	0.044
	(0.196)	(0.301)	(0.131)	(0.206)
Education: Ph.D.	0.049	0.080	0.036	0.050
	(0.216)	(0.271)	(0.186)	(0.218)
N	5,098	45,408	95,722	146,228
Percent	3.50%	31.10%	65.50%	100%

Note: Standard deviations in parentheses.

Among those with an associate degree or less, men have higher licensure rates than women, but the reverse is true among those with a bachelor's degree or higher. In both samples, married respondents and those with dependents are disproportionately more likely to hold a credential than single respondents and respondents without dependents. We also note that the overall credentialing rate for both licenses and certifications is higher for those with bachelor's degrees than for those at the sub-baccalaureate level. This is particularly true for licenses; note that several occupations that require more than a bachelor's degree also require a license (e.g., lawyer, doctor).

Figure 1 presents the averages for the outcomes we are evaluating in this paper. Here we observe higher rates of employment and higher hourly wages among credential holders and those having a bachelor's degree or higher. Wages are expressed as an hourly wage rate (or implicit hourly wage rate for salaried workers) for the respondent's primary job.

Figure 1: Average outcomes by credential status and degree level



Note: Certification refers to individuals with a certification but no license, while license refers to individuals with a license, whether or not they have a certification. Outcomes are not covariate-adjusted but are weighted using CPS survey weights.

5. Results

5.1. Main Results

Table 3 presents the first-stage regression results of the effect of the proportion of peers with a license on having an occupational credential. The *base controls* add in the county, month, and year fixed effects, the local peer group's mean wages, and other demographic variables, not including the gender, race, education, and age control variables (the demographic characteristics that define peer groups), which are added in the final "All controls" column. The *all controls* column shows the importance of controlling for these demographic variables independently, which are related to the peer group licensure rates. The coefficients in the first stage remain highly significant and large in magnitude but decrease as more controls are added. As an example of the magnitude of the effect, among sub-baccalaureate, going from a local peer group with a 12.9% licensure rate (the mean peer group average) to one with a 22.9% licensure rate is associated with a 5.92 percentage point increase in the likelihood of that individual obtaining a license—a sizeable increase. The instruments are strong, with F-statistics often in the hundreds, and never below 20.

Table 3: First-stage regressions of having a credential

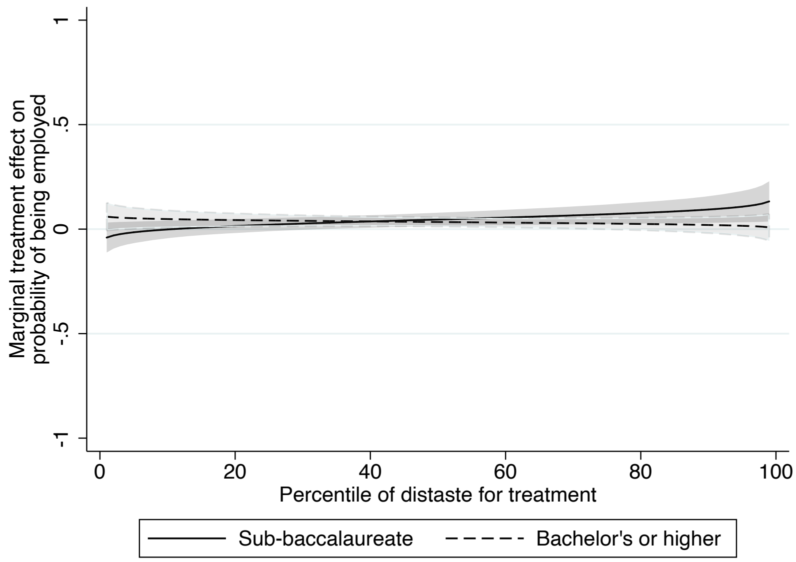
	License			Certification		
	No controls	Base controls	All controls	No controls	Base controls	All controls
Sub-baccalaureate	0.798***	0.659***	0.425***	0.489***	0.239***	0.198***
	(0.012)	(0.019)	(0.023)	(0.023)	(0.029)	(0.030)
	[5504.5]	[1982.7]	[192.6]	[802.2]	[353.4]	[45.0]
At least bachelor's	0.810***	0.615***	0.422***	0.404***	0.232***	0.207***
	(0.021)	(0.024)	(0.026)	(0.030)	(0.036)	(0.036)
	[3160.8]	[646.5]	[199.4]	[227.1]	[49.4]	[21.2]

Note: Each coefficient comes from a separate regression. Regressions labelled "base controls" include state and month fixed effects, and average local peer earnings. "All controls" specifications additionally include birth cohort indicators (e.g., millennials, generation-X, and baby boomers), race-ethnicity indicators, highest education indicators, marital status, having dependents at home, controls for local labor conditions (employment rate, average earnings, labor force participation). Clustered bootstrapped standard errors in parentheses, F-statistics in square brackets. ***p<0.01, **p<0.05, *p<0.1

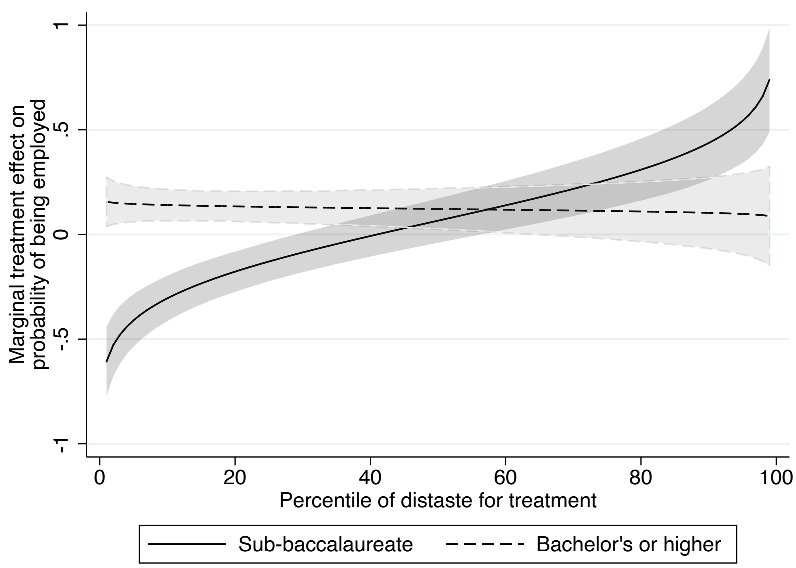
We next move to the second-stage results, starting with the returns to employment conditional on being in the labor force. Figure 2 presents the MTE returns curves. These plots provide a visual depiction of selection into treatment via the instrument. These curves are plotted over the distribution of "resistance to treatment"—in our case, how *unlikely* someone is to obtain a credential by virtue of having a highly-credentialed network. If the most positive returns are concentrated with those who easily comply with the treatment—who are very likely to obtain a credential when their peers are credentialed—then this is a case of positive selection. Postive selection is reflected in a downward slope of the MTE curve, where the most positive effects occur low in that resistance distribution. In contrast, if the graph slopes upward, this is indicative of negative selection. An upward slope means that the strongest returns are concentrated among those least propensed to obtain a credential in the way our instrument suggests: due to having a highly-credentialed network.

Figure 2: Marginal treatment effects of probability of being employed, conditional on being in the labor force

(a) License



(b) Certification



Note: Shaded region represents 95% confidence interval from clustered bootstrapping. Results come from estimating MTE model of the marginal impact of credentialing across distaste for treatment on the outcome of probability of being employed.

For licenses, we find small, generally positive effects on employment (the curve tending to have positive values). The sub-baccalaureate curve slopes upwards, consistent with negative selection into treatment—those with the highest distaste for treatment (the far right of the x-axis) have the most to gain in outcomes, but are least likely to get the treatment due to that distaste. This negative selection into treatment results in a LATE estimate (via 2SLS or MTE) that is lower than the ATE, because restricting the estimate to only compliers omits the non-compliers with potentially more positive effects. For baccalaureate license-holding, the slope is still upward, but much more shallow, such that there is not strong selection on distaste for treatment (note the similarity between LATE and ATE). Returns are strongest for those with the greatest distaste for treatment, which includes those least moved by our instrument.

For certifications, we see much stronger differences between sub-baccalaureate and baccalaureate populations. The graph suggests negative returns to employment for sub-baccalaureate workers most incentivized by peer credentialing (with the negative selection evidenced by a strong upward slope and an ATE much larger and more positive than LATE), while for the baccalaureate population, there are positive returns for all workers but particularly for those with little resistance for treatment (positive selection, slight downward slope, LATE larger than ATE).

Table 4: Effect of credentials on employment, conditional on being in the labor force

	License		Certification	
	Sub-baccalaureate	Bachelor's or higher	Sub-baccalaureate	Bachelor's or higher
OLS	0.020***	0.012***	0.011***	0.004*
	(0.001)	(0.001)	(0.003)	(0.002)
2SLS	0.053**	0.030**	-0.359***	0.194***
	(0.021)	(0.014)	(0.077)	(0.045)
ATT	-0.012	0.044**	-0.450***	0.134***
	(0.023)	(0.018)	(0.062)	(0.045)
ATUT	0.058***	0.028**	0.082	0.121**
	(0.019)	(0.013)	(0.055)	(0.053)
LATE	0.017	0.036***	-0.469***	0.152***
	(0.018)	(0.012)	(0.067)	(0.041)
ATE	0.149***	0.039**	0.372***	0.022
	(0.031)	(0.015)	(0.122)	(0.060)

Note: Each column comes from a separate regression. Regressions also include state and month fixed effects, birth cohort indicators (e.g., millennials, generation-X, and baby boomers), race-ethnicity indicators, highest education indicators, indicators for gender, marital status, and having dependents, local unemployment rate, local average earnings, local labor force participation rate, and local peer group earnings. Clustered bootstrapped standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1

All of the point estimates of treatment effects are weighted averages of these MTE curves. For comparison, we also present the LATE estimates that come from using the same instrument but using Two-Stage Least Squares (2SLS) instead of MTE. Note, 2SLS uses a linear probability model in the first stage, compared to a probit model for the LATE in the MTE model. Table 4 presents the estimates corresponding to Figure 2, as well as the OLS and 2SLS estimates for comparison. We identify, on average, positive employment effects of licensure as well as positive effects of certification for sub-baccalaureate workers. As indicated by the MTE plots, sub-baccalaureate workers most likely to obtain licenses or certifications due to peer group influence are actually *less* likely to benefit from this credential than those who are more resistant—the ATT is negative, but the ATUT is positive. We also find positive employment effects on the untreated population among bachelor's degree holders for both credential types.

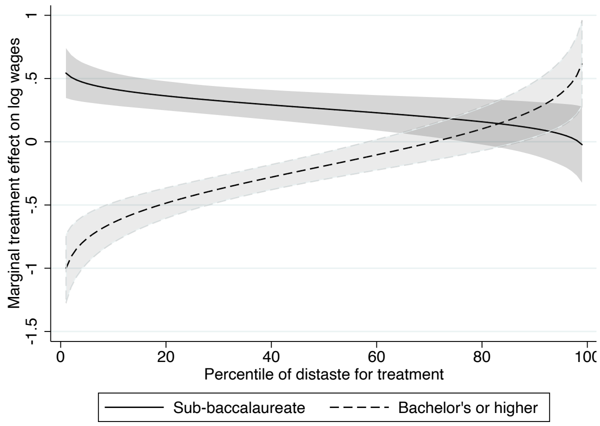
By construction, the 2SLS estimate is a weighted average of LATEs. However, LATEs (and consequently, 2SLS estimates) can differ considerably from ATEs when there is heterogeneity in treatment response that is correlated with selection into treatment. As shown by the second panel in Figure 2, there is profound negative selection into obtaining a certification for sub-baccalaureate populations, leading to a locally negative result (i.e., negative LATE and 2SLS) but an overall positive effect for certifications for sub-baccalaureate.

Figure 3 presents the returns to log wages, both with and without occupation and industry fixed effects. The sub-baccalaureate population has positive selection in all four models, indicated by the downward-sloping curve, while people with bachelor's degrees or higher have generally negative selection. The negative selection for the bachelor's or higher models may reflect the presence both of low-earning credentialed jobs that require bachelor's degrees, such as teaching, social work, and nursing, as well as several high-earning non-credentialed jobs for individuals with at least bachelor's degrees, including business management and several STEM occupations.

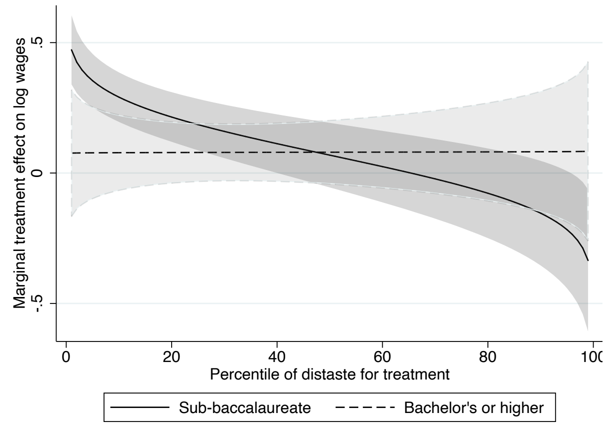
Table 5 presents the resulting averages of the MTEs across the models for log wages. For both credential types and education levels, the ATE are closer to zero and do not maintain statistical significance when occupation and industry fixed effects are included. Without occupation and industry fixed effects, part of the identified treatment effect may include credentialed individual's increased ability to transition into higher-paying occupations compared to a non-credentialed individual. This arguably represents a more complete treatment effect, reflecting another dimension of credentials' returns.

Figure 3: Marginal treatment effects of log wages, conditional on being employed

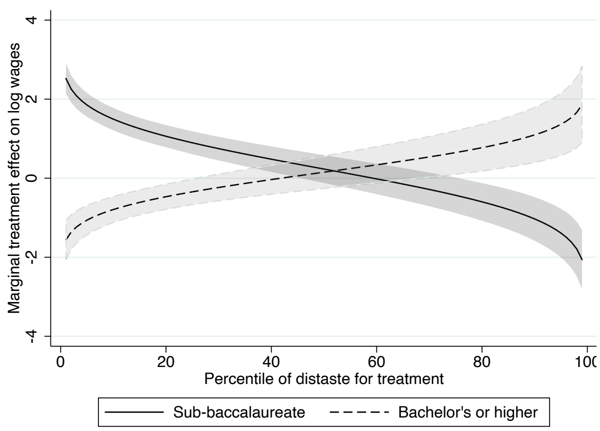
(a) License, no occupation or industry controls



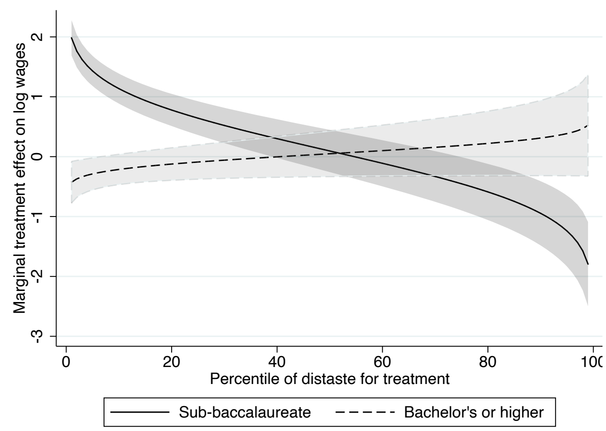
(b) License, occupation and industry controls



(c) Certification, no occupation or industry controls



(d) Certification, occupation and industry controls



Note: Shaded region represents 95% confidence interval from clustered bootstrapping. Results come from estimating MTE model of the marginal impact of credentialing across distaste for treatment on the outcome of probability of being employed.

While the model that includes industry and occupation fixed effects only identifies the increase in wages within industries and occupations (that is, not accounting for the credential's impact on their ability to transition to higher paying industries and occupations), the model that includes the fixed effects may better isolate the effect of credential holding in differentiating candidates in the same industry pursuing the same job. The ATEs are largest for sub-baccalaureate workers at around 0.25, or a 25 percent earnings increase. This is significantly larger than prior cross-sectional estimates of a 10 to 18 percent increase (c.f. Kleiner and Krueger, 2010; Kleiner and Krueger, 2013; Kleiner and Vorotnikov, 2017).

Table 5: Effects of credential-holding on log wages

	License				Certification			
	Sub-baccalaureate		At least bachelor's		Sub-baccalaureate		At least bachelor's	
	No occupation or industry controls	Occupation and industry controls	No occupation or industry controls	Occupation and industry controls	No occupation or industry controls	Occupation and industry controls	No occupation or industry controls	Occupation and industry controls
OLS	0.095***	0.072***	0.079***	0.063***	0.138***	0.090***	0.099***	0.063***
	(0.004)	(0.004)	(0.006)	(0.005)	(0.008)	(0.008)	(0.008)	(0.008)
2SLS	0.383***	0.453***	-0.489***	-0.644***	1.785***	1.511***	-0.147	-0.424**
	(0.062)	(0.068)	(0.059)	(0.086)	(0.178)	(0.172)	(0.204)	(0.187)
ATT	0.422***	0.329***	-0.539***	0.121*	1.889***	1.435***	-1.146***	-0.287**
	(0.067)	(0.045)	(0.070)	(0.066)	(0.144)	(0.108)	(0.191)	(0.129)
ATUT	0.227***	0.015	-0.006	0.057	0.181	0.053	0.231	0.069
	(0.073)	(0.072)	(0.075)	(0.086)	(0.184)	(0.185)	(0.222)	(0.206)
LATE	0.372***	0.241***	-0.334***	0.067	2.011***	1.583***	-1.003***	-0.257**
	(0.060)	(0.046)	(0.052)	(0.055)	(0.159)	(0.125)	(0.178)	(0.122)
ATE	0.260***	0.069	-0.192***	0.080	0.232	0.095	0.152	0.049
	(0.065)	(0.063)	(0.054)	(0.062)	(0.180)	(0.180)	(0.211)	(0.196)

Note: Each column comes from a separate regression. Additional covariates include state fixed effects as well as month fixed effects, birth cohort indicators (e.g., millennials, generation-X, and baby boomers), race-ethnicity indicators, highest education indicators, indicators for gender, marital status, and having dependents, local unemployment rate, local average earnings, potential experience as a quadratic, inverse mills ratio for employment, local labor force participation rate, and local peer group earnings. Clustered bootstrapped standard errors in parentheses. ***$p<0.01$, **$p<0.05$, *$p<0.1$

However, the ATE is not significant for certifications, where the variance in quality (and labor market returns) is likely much higher than for licenses, leading to noisier estimates. As discussed above, here too we presume that the negative ATE we find for licenses for bachelor's degree or higher is indicative of the presence of several low-paying licensed jobs among this population (e.g., teachers) and high-paying jobs that are not licensed (e.g., management). This interpretation is supported by the fact that the same model, once occupation and industry fixed effects are added, produces a positive, albeit insignificant, coefficient. Note that in prior cross-sectional work, Kleiner and Vorotnikov (2017) find a significant certification earnings premium of approximately 9 percent, very similar to our (insignificant) estimate with fixed effects.

5.2. Earnings Effect Decomposition

We next turn to the decomposition of the returns on hourly wages. Here we use hourly wages in place of log wages for ease of interpretation of the decomposition. For succinctness, we only present the OLS, 2SLS, and the ATE from the MTE model. Table 6 presents these results. For sub-baccalaureate licenses, approximately three quarters of the total effect comes from the extensive margin (increased likelihood of working, which yields wages) and one quarter from the intensive margin (higher earnings). For bachelor's or higher, the only positive and significant effect is for licenses on the extensive margin: workers are more likely to be employed because of their license, but have no subsequent pay increase of significance. Note that this is the model which includes occupation and industry fixed effects, which impacts the non-return on wages.

5.3. Instrument Validation with Associate Degree Return

We are able to construct a parallel local peer group instrument for the returns to an associate degree for the sub-baccalaureate population. Specifically, we estimate the fraction of people in the same demographic group in the CBSA that have an associate degree and repeat the MTE analysis for those with an associate degree or less. This serves two valuable purposes for our study. First, we can compare our estimate of the returns to education for traditional academic degrees already established in the literature. This allows a validation check of our instrument choice and MTE approach. Second, it allows us to compare for the same sample the returns to an associate degree to the returns to a license or to a certification, as a potential alternative educational pathway.

Table 6: Decomposed and total effects of credentials on hourly wages

		License			Certification		
		Extensive	Intensive	Total	Extensive	Intensive	Total
Sub-baccalaureate	OLS	0.174***	0.044	0.218***	0.103***	0.074	0.177**
		(0.037)	(0.044)	(0.062)	(0.038)	(0.066)	(0.072)
	2SLS	0.452**	0.280*	0.732***	-3.317***	1.106***	-2.194**
		(0.193)	(0.154)	(0.242)	(0.858)	(0.224)	(0.870)
	ATE	0.397***	0.013	0.410**	0.608	-0.460**	0.145
		(0.152)	(0.069)	(0.165)	(0.561)	(0.218)	(0.607)
At least bachelors	OLS	0.267***	0.003	0.269***	0.101*	-0.016	0.085
		(0.049)	(0.038)	(0.062)	(0.058)	(0.054)	(0.078)
	2SLS	0.676**	-0.023	0.652	4.682***	0.031	4.712***
		(0.338)	(0.223)	(0.413)	(1.060)	(0.218)	(1.074)
	ATE	0.768***	-0.003	0.765***	2.944**	0.024	2.968**
		(0.277)	(0.069)	(0.280)	(1.146)	(0.178)	(1.171)

Note: The extensive margin is the effect on overall wages driven by changes in the likelihood of being in labor force and probability of being employed, and the intensive margin is the effect driven by changes in wages conditional on working. Each coefficient comes from a separate regression. Additional covariates include state and month fixed effects, birth cohort indicators (e.g., millennials, generation-X, and baby boomers), race-ethnicity indicators, highest education indicators, indicators for gender, marital status, and having dependents, local unemployment rate, local average earnings, potential experience as a quadratic, inverse mills ratio for employment, local labor force participation rate, and local peer group earnings. Clustered bootstrapped standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1

The results are presented in Table 7. For convenience, we repeat the license and certification results from Table 5. The return to an associate degree is 0.16 using OLS and 0.21 for ATE. Lang and Weinstein (2013), using cross-sectional OLS, estimate a return to an associate degree that ranges 0.1 to 0.18 depending on the major, and Dadgar and Trimble (2015) use individual fixed effects and find estimates between 0.02 and 0.09, putting our OLS estimate on the higher end (likely because we are unable to include individual fixed effects). More causal estimates put the return around 0.15 log points per year (see Oreopoulos and Petronijevic, 2013) for about a 30-log point increase, putting our ATE estimate of the 2-year degree slightly smaller than this literature. This serves to validate our instrumental variable choice and modeling approach, both in range of estimates from the OLS versus the ATE estimate and the increase in coefficients in moving from OLS to ATE.

However, the estimates using the same instrument for the more-traditional 2SLS approach are perhaps implausibly large. We recognize that there is substantial treatment effects heterogeneity in the returns to education (see Balestra and Backes-Gellner, 2017). If the value of a credential stems from signaling, the credential is most valuable to those close to the inflection point in a separating equilibrium. Those who would always obtain a credential (regardless of peer influence) are likely to benefit less from this signaling premium, but they are excluded from the "local" treatment effect estimated by 2SLS. Consistent with the positive selection identified among the sub-baccalaureate population previously, our average treatment effect estimates, which include a broader range of individuals, are considerably smaller. This reinforces the importace of our using the MTE approach with this instrument, which allows us to generalize away from the local estimate.

Table 7: Comparison of log wage returns to associate degree using our instrumental variable to returns to certification and licenses for sub-baccalaureate population

	License	Certification	Associate degree
OLS	0.095***	0.138***	0.164***
	(0.004)	(0.008)	(0.004)
2SLS	0.383***	1.785***	1.250***
	(0.062)	(0.178)	(0.077)
ATE	0.260***	0.232	0.251***
	(0.065)	(0.180)	(0.036)

Note: each column comes from a separate regression Additional covariates include state fixed effects as well as month fixed effects, birth cohort indicators (e.g., millennials, generation-X, and baby boomers), race-ethnicity indicators, highest education indicators, indicators for gender, marital status, and having dependents, local unemployment rate, local average earnings, potential experience as a quadratic, inverse mills ratio for employment, local labor force participation rate, and local peer group earnings. Clustered bootstrapped standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1

Table 7 also shows that the ATE is very similar between the return to license, return to certification, and return to associate degree, all around 25%. Of course, certain credentials will require formal schooling such as would happen through an associate degree. Nonetheless, these results are suggestive of the potential for occupational credentials to serve as viable alternative educational pathways leading to higher paying jobs.

5.3. Returns by Gender

Lastly, we hypothesize that occupational credentials will bolster the labor market prospects of women more so than for men. This is partially supported in our analysis. As shown in Table 8, we find that our employment effects are almost entirely driven by women for three of the four cases, with significant increases in employment for female sub-baccalaureate workers holding licenses or certifications as well as for female baccalaureate workers holding licenses. In contrast, the only significant employment effect for men is concentrated among certification-holders with at least a bachelor's degree.

Table 8: Effects of credential-holding on employment by gender

	License		Certification	
	Sub-bac	BA+	Sub-bac	BA+
Men				
OLS	0.019***	0.011***	0.011***	0.003
	(0.002)	(0.002)	(0.004)	(0.003)
2SLS	-0.000	0.020	-0.301***	-0.049
	(0.030)	(0.024)	(0.101)	(0.065)
ATE	0.025	0.018	0.078	0.234***
	(0.027)	(0.019)	(0.071)	(0.082)
Women				
OLS	0.022***	0.013***	0.011**	0.005
	(0.002)	(0.001)	(0.005)	(0.003)
2SLS	0.235***	0.033*	-0.434***	0.501***
	(0.035)	(0.018)	(0.128)	(0.081)
ATE	0.149***	0.039**	0.372***	0.022
	(0.031)	(0.015)	(0.122)	(0.060)

Note: Each column by gender comes from a separate regression. Additional covariates include state fixed effects, month fixed effects, birth cohort indicators (e.g., millennials, generation-X, and baby boomers), race-ethnicity indicators, highest education indicators, indicators for marital status and having dependents, local unemployment rate, local average earnings, local labor force participation rate, and local peer group earnings. Clustered bootstrapped standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1

For earnings, we see the opposite story (Table 9). The only positive and significant earnings effects accrue to men—specifically, to men with licenses, and to men with a bachelor's degree and a certification. For women, we actually find evidence of *negative* returns to credentials, and these negative effects generally are not eliminated by accounting for industry and occupation. Together, these results suggest that for women, occupational credentialing matters in terms of hiring but not necessarily in terms of compensation.

Table 9: Effects of credential-holding on log wages by gender

	License				Certification			
	Sub-baccalaureate		At least bachelor's		Sub-baccalaureate		At least bachelor's	
	No occupation or industry controls	Occupation and industry controls	No occupation or industry controls	Occupation and industry controls	No occupation or industry controls	Occupation and industry controls	No occupation or industry controls	Occupation and industry controls
Men								
OLS	0.087***	0.072***	0.018**	0.027***	0.145***	0.087***	0.081***	0.052***
	(0.005)	(0.005)	(0.009)	(0.008)	(0.009)	(0.008)	(0.012)	(0.012)
2SLS	0.049	0.103	-0.348***	-0.193	0.579***	0.479**	-0.525*	-0.997***
	(0.092)	(0.092)	(0.110)	(0.144)	(0.220)	(0.205)	(0.277)	(0.262)
ATE	0.131	0.166*	0.193	0.314***	-0.615**	-0.419	0.542	0.886***
	(0.103)	(0.097)	(0.122)	(0.114)	(0.258)	(0.267)	(0.357)	(0.329)
Women								
OLS	0.096***	0.064***	0.128***	0.092***	0.119***	0.087***	0.121***	0.079***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.017)	(0.015)	(0.013)	(0.012)
2SLS	-0.095	-0.124	-0.342***	-0.542***	-0.898***	-0.836***	0.025	-0.510*
	(0.086)	(0.107)	(0.074)	(0.107)	(0.301)	(0.290)	(0.312)	(0.287)
ATE	-0.086	-0.739***	-0.179***	0.047	-0.030	-1.660***	-0.210	-0.560**
	(0.100)	(0.103)	(0.063)	(0.059)	(0.340)	(0.353)	(0.279)	(0.268)

Note: each column by gender group comes from a separate regression. Additional covariates include state fixed effects as well as month fixed effects, birth cohort indicators (e.g., millennials, generation-X, and baby boomers), race-ethnicity indicators, highest education indicators, indicators for gender and having dependents, local unemployment rate, local average earnings, potential experience as a quadratic, inverse mills ratio for employment, local labor force participation rate, and local peer group earnings. Clustered bootstrapped standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1

6. Conclusion

Occupational credentials, whether licenses or certifications, provide an additional and at times important alternative path other than traditional academic degrees for individuals to increase productivity as well as signal their ability and qualifications to employers. This may be particularly important for workers in the sub-baccalaureate labor market and for women. However, the evidence of the returns to licenses and certifications is limited, with most prior research having limited causal identification relying on cross-sectional OLS regressions. Using data on credential receipt from the 2015 and the 2016 Current Population Surveys and constructing a new instrumental variable of the within-CBSA credential rate of individual's demographic peer groups, we identify the effect of licenses and certifications on labor market outcomes. We use our instrument to estimate the distribution of treatment effects through a marginal treatment effect estimator. Given the large difference in what form these licenses and credentials take depending on the education level of the credential holder, we conduct all analyses separately for sub-baccalaureate and bachelor's degree populations.

Our analysis yields a number of findings of note. First, we find large, meaningful returns for probability of employment conditional on being in the labor force. Both OLS and 2SLS significantly underestimate the employment returns to credentials for sub-baccalaureate workers due to the negative selection into having a credential. The estimated effects for sub-baccalaureate workers are larger and more consistently significant for both licenses (ATE of around 15 percent increased probability of employment, compared to 4 percent for bachelor's or higher) and certifications (37 percent compared to an insignificant 2 percent for bachelor's or higher). This often-overlooked return to credentials also thus plays an important role on increased overall earnings, accounting for the majority of earnings increase in our decomposition, compared to wage increases given employment, when controlling for occupation and industry fixed effects. This suggests that occupational credentials act as an important signal to employers in the hiring process, especially for those with less than a bachelor's degree – which is not altogether surprising as those lacking a bachelor's degrees often need to differentiate themselves from other job applicants and workers in terms of the types of knowledge, skills, and abilities they can bring to employers.

Second, we find that compensation for the acquisition of an occupationl credential can be substantial. If we take a back-of-the-envelope weighted averaging of our effects for all education groups to mirror the literature (2/3rds of the sub-baccalaureate estimate plus 1/3rd of the bachelor's or higher estimate), we find an estimate of around 11 percent return to a license, reduced to 7 percent when occupation and industry fixed effects are included. These estimates are by and large consistent with those observed in other studies (Albert, 2017; Gittleman et al., 2018; Ingram, 2019; Kleiner and Krueger, 2013). However, this average covers a large difference in the return to a license for sub-baccalaureate workers (26 percent) and those with a bachelor's degree or higher (-19 percent). This is an important distinction of the role that licenses can play for increasing earnings. Additionally, these returns are from the models which do not include occupation and industry fixed effects; once those are included, the returns between the two educational groups converge to around 7-8 percent for both education groups. We interpret the findings to suggest that for sub-baccalaureate workers, while there is a within-industry/occupation increase in earnings from having a license, the majority of the return to earnings comes from the ability to transition into occupations and industries that have higher earnings. The reverse is true for those with a bachelor's degree or higher, where there is wage loss from licenses leading to jobs in lower-paying industries and occupations, such as teaching, the effect of which disappears when looking at earnings changes within occupation/industry. These nuances are novel contributions to the literature, and reveal complexities that should be considered when evaluating the role of occupational credentials as sorting mechanisms in the labor market.

Third, we find that occupational credentials shape labor force outcomes differently for women then for men. Our identified employment effects are concentrated among women while our identified earnings effects are concentrated among men. The former highlights how occupational credentials can serve as a meaningful signal of women's human capital when they are seeking employment. However, the latter suggests that despite their utility during the hiring process, occupational credentials do not attenuate long-standing gender gaps in earnings, which is in contrast to the findings identified by Blair and Chung (2017).

There are limitations to this research. Instrumental variables rely on limiting the variation in the endogenous variable. While this limiting removes the bias when the assumptions hold, it nonetheless reduces the power of the analysis. Also, instrumental variables are typically only able to estimate the LATE for those impacted by the instrument; in our case we are able to identify the ATE, but this is based on the assumption that the MTE model is correct, including in our case the parametric form of the estimated returns curve with respect to distaste for treatment. Additionally, we have data limitations, as the CPS questions do not allow us to distinguish between those with licenses but no certifications separately from those with licenses and certifications. It also does not reveal the precise credential obtained, nor the total number of credentials held. This limits the conclusions that we can draw from the analysis. Further, our analysis uses data from 2015 and 2016; these were strong years for the United States economy, and the returns may be larger than in less robust economic years with slack labor markets.

In closing, our analysis contributes new information to the growing research base on occupational credentials as a distinct market of human capital in the labor market. Overall, we find that the attainment of occupational credentials is beneficial both in terms of employment and earnings. These credentials are particularly beneficial for those in the sub-baccalaureate labor market, and the increased ability to find any work, and to transition into occupations and industries with higher pay, given their credential. Altogether, the findings from this paper highlight the benefit of both licenses and certifications for this population, and their role as viable alternative and/or complementary educational pathways for those not seeking a bachelor's degree.

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