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Certifiably employable? Occupational regulation and unemployment duration

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Abstract

Occupational regulation is a labor market institution that has received a growing amount of attention. However, there is a gap in the literature regarding the relationship between occupational credentials and unemployment duration in the United States. Thus, we propose a random search model to explain differences in unemployment duration resulting from heterogeneous effects from licenses and certification. Our model predicts that an occupational credential with a stronger signaling/human capital effect results in a shorter individual unemployment duration. To estimate the relationship between occupational credentials and spells of unemployment, we perform a survival analysis using panel data from the Survey of Income and Program Participation (SIPP) for the years 2013–2019. We find that both licensing and certification are associated with reductions in unemployment spells for Black males that are similar in magnitude. Our results provide some suggestive guidance to policymakers since certification is less costly and not mandatory like occupational licensing.

KEYWORDS

certification, occupational licensing, occupational regulation, search, unemployment duration

JEL CLASSIFICATION

J64, E24

1 | INTRODUCTION

More than 20% of workers in the United States have an occupational license (Cunningham, 2019; Kleiner & Krueger, 2013). On average it has been estimated that 22% of workers in the European Union are also licensed (Koumenta & Pagliero, 2019). In the United States the fraction of workers licensed has grown fourfold over the last 50 years (White House, 2015) and as of 2018 more than 40 million people in the United States held either a professional license or certification (Cunningham, 2019).

Theoretically, occupational licensing is viewed as a form of rent-seeking (Friedman, 1962; Friedman & Kuznets, 1945) or a human capital enhancement with a restriction on low skilled substitutes (Shapiro, 1986). The signaling explanation of occupational licensing has been studied in Leland (1979) and in the context of Spence's (1978) model by Blair and Chung (2021, 2022).

This paper further studies the signaling aspect of occupational regulation with respect to unemployment duration through the lens of signaling and human capital. An occupational credential may open access to additional occupations by building skills needed for available jobs. At the same time, an occupational credential has the potential to send a signal to prospective employers of innate ability. Improvements in human capital and signaling can both be associated with shorter unemployment duration. We differentiate the effects of licensing—the strictest form of occupational regulation that makes it illegal to perform a job—from certification (Hemphill & Carpenter, 2016). Certification, a less restrictive form of occupational regulation, often prevents workers from using job titles (e.g., certified hairdresser).

Both licenses and certifications send a signal to employers (or enhance human capital) that a person possesses specific knowledge or skills to do the job. Both licenses and certifications expire if not renewed. The difference is that licenses are mandatory to do the job and issued by governmental licensing agencies—it is a crime to work in a licensed profession without obtaining the license. Certifications, on the other hand, are optional and can be issued by nongovernmental bodies. Licensing is very common in occupations in healthcare (doctors, nurses, and dentists to name a few), education (e.g., teachers), legal services (e.g., lawyers) and other service occupations (real estate brokers, hairdressers, and massage therapists). Certification, on the other hand, is common in the information technology (IT) sector (e.g., computer programmers), installation maintenance and repair (e.g., car mechanics), and other occupations such as human resource managers, project managers, graphic designers, financial analysts, and market research analysts.

In 2022, the Bureau of Labor Statistics reported that roughly 21% of the civilian labor force had a license while around 2% had certification. Out of unemployed people, 11% had a license and 1.5% had certification. Furthermore, out of the civilian labor force 55% and 54% of non-credentialed (not licensed and not certified) Whites and Blacks were employed while 3% and 7% were unemployed respectively. At the same time 86% and 84% credentialed Whites and Blacks were employed and 2% and 3.5% were unemployed respectively. Given these differences, some important observations emerge. If you have a license or certification, you are more likely to be employed. Second, licenses and certifications seem to be particularly useful for Blacks. The unemployment rate for Blacks with licenses and certifications is twice as low as for Blacks lacking these credentials. Given these differences, it is conceivable that it might be easier to find a job if you have a certification or a license—particularly for Black workers.

Given that we observe these differences in the data, what is the relationship between occupational regulation and unemployment duration? To better understand this relationship, we first develop a random search model to predict the effects of occupational credentials on unemployment duration. Our model predicts that the strength of an occupational credential in terms of human capital improvement and/or signaling is inversely related to individual unemployment duration. We then test the theoretical predictions of our economic model using an exponential survival setting. We correct for endogeneity that might come from a selection bias using the two step Heckman procedure. We perform a number of robustness checks, and our results are consistent.

Our results suggest that both licensing and certification are associated with reductions in individual unemployment duration for Black males. In line with wage estimations from Blair and Chung (2021), we find that licenses are associated with reductions in unemployment duration among Blacks. However, we also find that certification is equally effective at providing a signal to prospective employers.

Our paper contributes to several strands of literature. First, this paper is the first attempt to examine the relationship between occupational credentials and unemployment duration. Second, our paper contributes to the policy debate regarding the costs and benefits of differing forms of occupational regulation.

Our paper is organized as follows. After our review of the literature, Section 3 introduces a model of job search with occupational credentials. Section 4 contains a data description. Section 5 presents our empirical methodology. Before concluding our paper in Section 7 and discussing avenues for further research, we present our results in Section 6.

2 | LITERATURE REVIEW

Many studies have examined the possible causes of unemployment duration in existing literature. For example, there are studies that have investigated the relationship between unemployment duration and time, that is, the longer you're unemployed the less likely you become reemployed known as negative duration dependence (Blanchard & Diamond, 1994; Kroft et al., 2013), education (Kettunen, 1997), labor force attachment (Abraham & Shimer, 2001), unemployment benefits and business cycle (Bover et al., 2002; Lalive, 2008; Røed & Zhang, 2003), race (Dawkins et al., 2005), residential location (D'etang-Dessendre & Gaign'e, 2009), and personality traits (Uysal & Pohlmeier, 2011) to name a few. A seminal work on unemployment duration models is McCall (1996). For a review of the methodology see Kiefer (1988), and for more recent work see Chetty (2008) and Schmieder et al. (2016).

On the other hand, the relationship between occupational regulation and unemployment duration has not been explored. Over the past few decades, two trends in the U.S. labor market have become clear. The share of workers covered by licensing has been on the rise while labor union membership has been decreasing. (fig. 1, p. 679 in Kleiner & Krueger, 2010). For an overview of occupational licensing as a labor market institution see Kleiner (2000).

As noted in the introduction, occupational licensing can function as a barrier to entry into occupations (for a recent example see Yelowitz and Ingram (2021)). Licensing restricts entry by entry fees as well as setting minimum levels of education and work experience (through internships or apprenticeships). Some occupations like doctors are universally licensed in the United States and Europe (Nunn, 2016) whereas others like animal breeders and art therapists are licensed in only a few states (Carpenter et al., 2017; Norris et al., 2024). Thus, licensing requirements while being mandatory vary significantly from state to state as well as the city level in some cases (Deyo et al., 2021; Hall et al., 2019). For an example of public members on the licensing boards see Graddy and Nichol (1989) and for an example of how interest groups push for occupational licensing laws see McMichael (2017).

A large number of empirical studies have estimated the costs associated with occupational licensing.[1] Some studies have focused on particular occupations and estimated wage premiums for licensed barbers (Timmons & Thornton, 2010), lawyers, massage therapists (Thornton & Timmons, 2013), opticians (Timmons & Mills, 2018), radiologic technologists (Timmons & Thornton, 2008), and real estate agents (Chung, 2022). Other studies have estimated the effects of licensing across all occupations and have estimated wage premiums ranging from 6% to 18% in the United States (Gittleman et al., 2018; Gittleman & Kleiner, 2016; Ingram, 2019; Kleiner & Krueger, 2010, 2013). Recent work suggests that the effects of licensing may take some time to be realized in the labor market due to grandfather provisions (Han & Kleiner, 2021). Licensing is also found to reduce labor supply measured using market shares of occupations on a state level by an average of 17%–27% (Blair & Chung, 2019), increase education time, increase wages, reduce employment, and overall decrease welfare (Kleiner & Soltas, 2023).

The effects of licensing have also been studied outside of the United States. In Australia, licensing is found to raise wages for licensed occupations, but has negative effects on unlicensed occupations (Tani, 2021). For Europe, the effect of licensing on wages is estimated to be 4% (Koumenta & Pagliero, 2019). For China, wages increase by 15% as a result of licensing (Chi et al., 2017).

Theory also suggests that licensing may improve the quality of services delivered to consumers. However, existing evidence of the effects of licensing on the quality of services is more mixed. For instance, (Carroll & Gaston, 1981) found a negative association between per capita number of practitioners in an occupation and per capita measure of quality. Kleiner and Kudrle (2000) also find no effect on quality for dental health practitioners. Maurizi (1980) found mild positive effect for building contractors whereas Carpenter (2012) found no effect on the quality of florists. At the same time, the licensing of midwives at the turn of the 20th century in the United States reduced maternal mortality by 7%–8% (Anderson et al., 2020).[2] More recent licensing of electricians had no effect on injuries and death rates among those practitioners (Kleiner & Park, 2014). More recently, it has been found that licensing status bears no effect on consumer ratings in online platforms (Farronato et al., 2020).

Labor market fluidity is also affected by licensing where licensed workers are 24% less likely to switch occupations and 3% less likely to become unemployed the following year (Kleiner & Xu, 2024). Finally, licensing also affects entrance exam difficulty (Pagliero, 2013) as well as firm location choices by raising labor requirements and fees and driving firms to states with lower costs (Plemmons, 2022).

In this paper, we contribute to the existing literature by focusing on the relationship between occupational credentials and unemployment duration. We begin by developing a random search model that derives conditions for heterogeneous associations of occupational credentials and individual unemployment duration. We then test the results of our model using an exponential survival analysis. We perform a number of robustness checks, and our results are consistent.

[1]Perhaps owing to the paucity of de-licensing (Thornton et al., 2021; Thornton & Timmons, 2015), considerably less is known about the effects of removing occupational licensing (Pizzola & Tabarrok, 2017; Timmons & Thornton, 2019).
[2]For earlier discussion on midwifery licensing see Adams III et al. (2003).

3 | A MODEL OF JOB SEARCH WITH OCCUPATIONAL CREDENTIALS

To study the effects of occupational credentials on unemployment duration, we derive our model from the seminal work of Mortensen (1977). In his article, Mortensen (1977) proposes a random search model that helps explain how unemployment benefits and the prospects of future layoffs affect job search and unemployment duration. One of the main conclusions is that unemployment benefits can create disincentives to look for jobs, but the prospect of future layoffs and eligibility for unemployment benefits create incentives to search for jobs, leading to ambiguity in the sign of the effect of unemployment benefits on unemployment duration.

Conceptually, our model of job search with occupational credentials augments the Mortensen (1977) model by allowing workers to have various occupational credentials that open job opportunities and increase the probability with which new job offers arrive, accounting for heterogeneity in reservation wages across occupational credentials. Following Mortensen (1977), we define the escape rate as the probability that an offer arrives multiplied by the probability that the offer is acceptable, that is, the transition into the new state of a newly accepted job. Unemployment duration is inversely related to the escape rate. Heterogeneity in licensing and certification relative to unemployment duration arises from differences in expected frequencies with which workers find acceptable offers. As in Mortensen (1977), escape rate from being unemployed is q. Escape rate q is defined as a product of a probability that an offer arrives and probability that an offer is acceptable.

$$q = \Pr(\text{offer}) \times \Pr(\text{accept}). \tag{1}$$

Assume a time interval h. An individual is searching for a job with a search intensity s and $\Pr(\text{offer})$ is proportional to the time devoted to search with a parameter α denoting that proportion i.e.,

$$\Pr(\text{offer}) = \alpha s h. \tag{2}$$

Our model differs from Mortensen (1977) in two ways. First, we assume that the $\Pr(\text{offer})$ is influenced by a market signal μ coming from a credential. The higher the signal, the greater the probability that an offer will arrive. The source for a market signal can be viewed as a cost associated with investment in licensing as in Spence (1978) or Blair and Chung (2021). Sometimes a signal can come from background checks that might be part of the licensing application procedure as detailed in Blair and Chung (2022).

Second, the parameter α is the extent to which an individual who searches for a job has access to different occupations. It is possible that an occupational credential, apart from the signaling, creates a path for an individual to an occupation that has its own labor market characteristics, that is, high/low tightness of the labor market that can result from equilibrium adjustments of supply and demand, geographical concentration, or deviation from perfectly competitive markets. All these characteristics can be captured by α. Adding heterogeneity across credentials that affect search intensities, signals, and access to labor markets, the probability that an offer arrives for credential j becomes:

$$\Pr(\text{offer})_j = \alpha_j \mu_j s_j h, \tag{3}$$

where $j = 1$ stands for licensing and $j = 2$ stands for certification. Next, we define the probability that an offer is acceptable. Let $F(w)$ be defined as the probability that a job offer will be below the worker's reservation wage. With no outside option, the probability of job acceptance will be equal to 1—there is no possibility of the job offer falling below the worker's reservation wage: $F(w) = 0$. With an outside option, for example an unemployment benefit, the probability of acceptance will be less than 1—in other words, $F(w) > 0$. Then the escape rate for credential j becomes as follows:

$$q_j = \alpha_j \mu_j s_j h \times [1 - F(w)]. \tag{4}$$

We then add heterogeneity across occupational credentials that affect the probability that an offer is acceptable. We assume that there are two wage-offer distributions $F_1(w)$ for licenses and $F_2(w)$ for certification. Moreover, since licensing increases wages in licensed occupations and certification is a less strict regime, we assume that those increases in wages are greater under licensing than under certification. For wage-offer distributions that implies that $F_1(w)$ first-order stochastically dominates $F_2(w)$.[3] To the best of our knowledge, there is no study that directly tests that assumption. However, papers by Kleiner and Krueger (2013) for the United States as well as Koumenta et al. (2022) for Europe indirectly support that assumption by providing evidence that the licensing wage premium is higher than the certification wage premium. Thornton and Timmons (2013) find similar evidence specifically for massage therapists. How occupational credentials affect reservation wages remains an empirical question.[4] Thus, the escape rate for credential j becomes as follows.

$$q_j = \alpha_j \mu_j s_j h \times \left[1 - F_j(w)\right]. \tag{5}$$

The optimization process occurs as in Mortensen (1977) where an agent determines optimal search intensity and reservation wage comparing marginal benefits and marginal costs of searching versus consuming leisure and accepting a job versus income stream from being unemployed resulting in optimal s^* and w^*. Then it is straightforward to show that escape rates will be greater for credentials with stronger human capital and signals adjusting for relative reservation wages and search efforts:

$$q_1 > q_2 \text{ if } \alpha_1 \mu_1 > \alpha_2 \mu_2 \frac{[1 - F_2(w^*)] s_2^*}{[1 - F_1(w^*)] s_1^*}, \tag{6}$$

$$D_j^0 = \int_0^\infty v q_j^0 \exp^{-q_j^0 v} dv = 1/_{q_j^0}. \tag{7}$$

The availability of unemployment benefits might affect individuals' reservation wages and hence unemployment duration. Mortensen (1977) distinguishes two cases of unemployment duration: one where a worker is not qualified for unemployment benefits and one where a worker is qualified. We will consider the case where a worker is not qualified for

[3]Thus $F_1(w) \leq F_2(w) = \Rightarrow 1 - F_1(w) \geq 1 - F_2(w)$.

[4]Reservation wages decline with unemployment duration (Kiefer & Neumann, 1979). Reservation wages are also affected by observable (Prasad, 2004) and unobservable characteristics (Caliendo et al., 2015; McGee, 2015).

unemployment benefits, but results are conceptually similar for the other case. Denote q^0 as the constant escape rate independent of unemployment duration. Let v be the probability distribution of the realized spell duration. As in Mortensen (1977), v is a negative exponential with expectation $1/q^0$. Thus, unemployment duration for an occupational credential j is presented in Equation (7). Here, the augmented model allows us to compare the heterogeneity in licensing and certification relative to unemployment duration through escape rate q_j^0. Thus, duration of workers who have a license is shorter than the duration of workers who have a certification if

$$D_1^0 < D_2^0 \text{ if } 1/q_1^0 < 1/q_2^0 \rightarrow q_1^0 > q_2^0. \tag{8}$$

In other words, if the escape rate for licensed workers is greater than the escape rate for certified workers, then the unemployment spell will be lower for licensed workers (and vice versa). We can denote q_0^0 as the escape rate for non-credentialed individuals for example assuming that signaling strength of no credentials is $\mu_0 = 1 < \mu_j$ where $j = 1, 2$. Thus, it is either $q_1^0 > q_2^0 > q_0^0$ or $q_2^0 > q_1^0 > q_0^0$. Graphically these results are presented in Figure 1. As shown in Figure 1, v is the length of the spell of unemployment duration. q_j^0 denotes the escape rate for individuals without unemployment benefits and $j = \{1, 2\}$ denotes an individual who has a license or a certification respectively. Compared to the escape rate for individuals without credentials q_0^0, panel (a) illustrates when individuals with licensing have an easier time finding a job and vice versa for panel (b). In the following sections we test whether gray lines are above the black line and whether gray lines are statistically different.

4 | DATA

In this section we describe our data set and how we constructed our sample. We also describe how we construct unemployment duration, the occupational credentials variables, and other

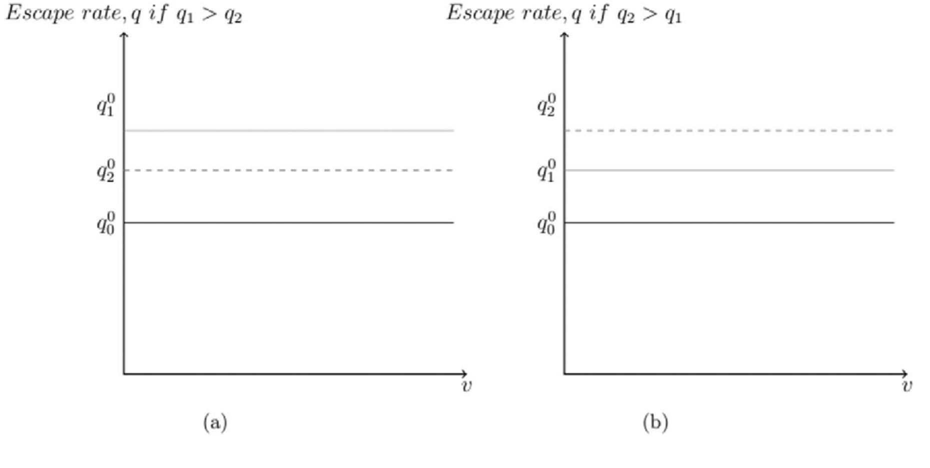

FIGURE 1 Comparison of relationship between escape rates and duration of unemployment for licensing and certification. q_0^0 is escape rate with no credential denoted as solid black line; q_1^0 is licensing and denoted with a solid gray line; q_2^0 is certification and denoted with a dashed gray line.

controls. To test the strength of licenses and certification, we use the Survey of Income and Program Participation (SIPP) panel database that collects data for the time period of 2013–2019 in the United States.[5] The SIPP is a nationally representative panel data set on employment, income, and program participation dynamics. For our analysis we use the SIPP 2014 Waves 1–4 and SIPP 2018–2020 panels. The four SIPP 2014 Waves cover 2013–2016 and the SIPP 2018 panel covers 2017. Like SIPP 2018, SIPP 2019 and SIPP 2020 also contain data for the preceding year. Each SIPP panel surveys households at 12-month intervals for 4 years. Some important advantages of the SIPP data are the availability of data on employment status, unemployment insurance benefit details, and large sample size. Most importantly for the purpose of our analysis, the survey asks participants whether they earned a professional certification or a license. Beginning with the 2014 panel, SIPP data are based on a new survey instrument, called SIPP-EHC or Event History Calendar, that changed the survey reference period from 4 months to 1 year. Each interview covers the previous calendar year plus the months leading up to the interview in the current calendar year (for details see SIPP source and accuracy statements). Thus, for each person in our sample we have at least 12 months of observations. Previous research has utilized the SIPP to examine the effects of licensing on wages and employment (Blair & Chung, 2022; Gittleman et al., 2018). We should further note that the SIPP data set is utilized by Chetty (2008) to examine unemployment duration and unemployment insurance, but this was prior to the addition of questions regarding occupational credentials.

In terms of the time period for our analysis, we focus on SIPP panels covering 2013–2019 for several reasons. First, the data are far removed from any lagging effects from the financial crisis of 2008, and do not contain any abnormalities in unemployment duration due to the COVID-19 pandemic. Second, as noted previously, starting with the 2014 panel the survey changed the reference period from 4 to 12 months and introduced the EHC. Finally, and critical to our analysis, this also reflects when the SIPP added a question regarding the licensing and certification status of survey respondents. The SIPP in total for this period contains 4,575,305 person-month observations. Following previous work by Chetty (2008) and Tatsiramos (2009), our sample criteria are as follows. First, we combine the household sample unit identifier[6] and a person number identifier[7] to create an individual specific identifier variable and then we restrict the sample to people aged 18–65.[8] Second, we refine the sample using employment status[9] in each month for each SIPP panel. Employment status in the SIPP can take one of the six following values:

1. With a job entire month, worked all weeks.
2. With a job all month, absent from work without pay 1+ weeks, absence not due to layoff.
3. With a job all month, absent from work without pay 1+ weeks, absence due to layoff.
4. With a job at least 1 but not all weeks, no time on layoff and no time looking for work.
5. With a job at least 1 but not all weeks, some weeks on layoff or looking for work.
6. No job all month, on layoff or looking for work all weeks.
7. No job all month, at least one but not all weeks on layoff or looking for work.

[5]We use Panel 2014 wave 1–4, Panel 2018, 2019, and 2020. These panels cover the time period of 2013–2019.

[6]Denoted as ssuid in the SIPP.

[7]Denoted as pnum in the SIPP.

[8]Following Chetty (2008) we don't impose wage restrictions on our sample which allows us to potentially include occupations with high wages such as surgeons. However, as a robustness check we restrict the sample to reported wages below $200 K a year to exclude wage outliers and our results are similar.

[9]Denoted as rmesr in the SIPP.

8. No job all month, no time on layoff and no time looking for work.

Following Chetty (2008, p. 230) we restrict our sample to workers that are coded 1, 2, or 3 in the first month that we observe them in the panel. In other words, we restrict our sample and our analysis to those who originally had a job but lost a job at some point during the period of analysis. That allows us to control for occupation fixed effects as in Chetty (2008) using previous occupation preceding a job loss. Third, we drop observations for individuals who were not in the panel for at least 3 months. Fourth, we drop people with gaps in observations.[10] Fifth, following Chetty (2008) and Tatsiramos (2009) we restrict analysis to males.[11] Next, we drop observations where individuals hold association certification and other certification.[12] Finally we focus on short term durations that are not longer than 6 months.[13] After making these adjustments to our sample, we are left with a total of 5037 unemployment spells, which comprises 29% of the cleaned initial sample[14]—very similar to the magnitude of observations used by Chetty (2008).

Unemployment duration is measured in months. Once a person experiences a job separation, unemployment duration starts and then a person either finds a job or stays unemployed until the end of the panel (right-censored spell) which is in line with Chetty (2008) approach.

Occupational credentials are either a license or certification. Individuals can have neither, either, or both.[15] Occupational credential variables are constructed as follows. The variable "license" is defined as a credential awarded by a governmental licensing agency.[16] This definition is consistent with the literature (Allard, 2016; Blair & Chung, 2022; Gittleman et al., 2018; Kukaev et al., 2020). The variable "certification" is defined as a credential awarded by a nongovernmental body.[17] In our case we focus on company certification. We do not include association certification and other certifications to avoid measurement ambiguity since many occupations in those credential categories are nurses and teachers or medical assistants which are common or universally licensed occupations.

Education is measured as follows. A person is a high school dropout if an individual's highest attained education is 12th grade and no diploma or less. A person has education denoted as high school if he is a high school graduate (diploma or GED or equivalent). A person has some college if he has some college credit and less than a year of college or 1 or more years

[10]For example, a person might be in a panel in 2013, 2014, and 2016 years with the 2015 year missing, so we drop those individuals.

[11]We acknowledge the importance of studying women in the labor markets, the reasons for focusing our analysis on males are as follows. First, males traditionally have higher attachment to the labor market. Second, there has been a secular decline of labor force participation of prime aged men in the United States in recent decades.

[12]We observed likely errors in the classification of individuals with certifications issued by associations and other organizations. Several of the individuals in each group are nurses and medical assistants, respectively, which are licensed occupations.

[13]Due to two important reasons. First, examining Kaplain-Meier survival functions we see that credentials are not strongly associated with unemployment reductions for long term unemployed, that is, for those whose duration is longer than 6 month which is the median duration. Second most states pay unemployment benefits for up to 6 months.

[14]Cleaned initial sample is the whole sample after we restrict age to 18–65 years, drop people who entered a panel without a job, drop people who didn't experience a job separation, drop people with fewer than 3 months observations, and drop people with gaps in observations. Cleaned initial sample is 26% of the initial raw sample of individuals who experienced unemployment duration with restricted age to 18–65 years.

[15]We only have three spells that have both a license and a certification. Results don't change if we exclude those.

[16]Denoted as *ewhocert1* in the SIPP.

[17]Denoted as *ewhocert3* in the SIPP.

of college and no degree. A person is coded as having a college degree and above if he has associate's, bachelor's, master's, professional, or doctorate degree.

Other variables are defined as follows. Age is defined as the age at the last birthday. An indicator for race is defined based on a question if a person considered himself to be White, Black, Asian, or another race. An indicator for immigrant is defined if a person is not a citizen of the United States. An indicator for receipt of unemployment compensation is based on whether a person received unemployment compensation payments within a month prior to finding a job or when the panel ends, whichever comes first. An indicator for being laid-off is defined based on whether the individual reported spending some time on layoff for a no-job spell associated with a month prior to finding a job or when the panel ends, whichever comes first. Occupation is defined based on a 4-digit occupation code in SIPP and is taken from the previous job before job separation. State is defined as the state of residence for the interview address. Year and month are defined as year and month prior to finding a job or when the panel ends, whichever comes first. Accounting for complex survey design, primary sampling units and strata for variance estimation are taken from SIPP as both half sample code and variance pseudo stratum code. Given the size of our licensed and certified sample, this is the preferred approach (Bye & Gallicchio, 1989).

Before turning to our sample analysis, let us summarize our expectations for our analysis. First, we expect to see an association between licensing and a reduction in unemployment duration among Black workers. This result would be in line with the statistical discrimination argument from Blair and Chung (2021). Based on our economic model (we expect escape rates for credentialed individuals in Figure 1 to be statistically different from escape rates for non-credentialled individuals), and differences we noted in the introduction between groups, however, we also expect that certification will also be associated with reductions in unemployment spells.

We further expect to see that credentials should only play a role for short term unemployment spells for two reasons. First, our literature review shows that time is a factor that negatively affects escaping unemployment which is known as negative duration dependance (Blanchard & Diamond, 1994; Kroft et al., 2013). The longer a person is unemployed the more difficult it is for a person to find a job. Thus, it is a common practice to differentiate between short-term or long-term unemployment (Abraham & Shimer, 2001; Kroft et al., 2016). The second reason is that unemployment benefits are paid for up to 6 months in most states. Thus, we focus on short-term unemployment duration that is no longer than 6 months.[18]

Descriptive statistics for our sample are presented in Tables 1–4 (More details in Table B1). Unemployment duration is measured in months. Table 1, Panels A and B show mean unemployment duration by race and education respectively. As shown in Table 1, Panel A, most of the sample population is White, and the second dominant group is Black. The average short-term unemployment spell is longer for minority groups compared to the majority group. Turning to Table 1, Panel B, the average short-term unemployment spell is shortest for college educated individuals and longest for high school dropouts.

Table 2 summarizes average unemployment duration for the two types of occupational regulation credentials. As shown in Table 2, workers with licenses and certification have shorter unemployment durations than individuals without occupational credentials. The shortest

[18]We include both complete spells that are 6 months and shorter as well as spells that are right-censored if a panel ends before the spell is completed.

TABLE 1 Male unemployment duration by race and education (number of spells = 5037).

	Share in the sample (%)	Mean unemployment duration (months)
Panel A		
White	80	2.41 (.05)
Black	11	2.51 (.18)
Asian	5	2.57 (.23)
Residual	4	2.50 (.30)
Panel B		
High school dropout	11	2.68 (.13)
High school	33	2.49 (.09)
Some college	21	2.56 (.12)
College and above	35	2.26 (.06)

Note: Weighted means and unweighted shares. 2013–2019 from the Survey of Income and Program Participation (SIPP) data. Standard deviation is given in parentheses. Unemployment duration is short-term, that is, no longer than 6 months and is measured in months.

TABLE 2 Male unemployment duration by occupational credentials (number of spells = 5037).

	License	Certification	None	Total
Mean unemployment duration	2.20	2.30	2.48	2.43
	(.08)	(.30)	(.05)	(.05)
Share in the sample (%)	14	2	84	100

Note: Weighted means and unweighted shares. 2013–2019 from the Survey of Income and Program Participation (SIPP) data. Standard deviation is given in parentheses. Unemployment duration is short-term, that is, no longer than 6 months and is measured in months.

unemployment duration, on average, is observed for individuals with licenses and then with certification.

A further breakdown by race for each credential group is shown in Table 3. As we can see from Table 3, the share of Whites is largest in the licensing sample. Interestingly, for certification the share of Whites is lower than the overall share of Whites in the sample. Table 4 contains comparisons for each credential group by education. Table 4 highlights that the unemployed who have a license are more educated, while the unemployed with certification have at most high school education more often than in other categories.

5 | EMPIRICAL METHODOLOGY

Equations (9) and (10) represent our econometric model. For the survival analysis, the survivor and hazard functions have the following forms, and we are interested in γ_j coefficients where $j=1$ stands for license and $j=2$ stands for certification. These two coefficients represent an association between occupational credential signaling strength and human capital improvement.

$$S(t)=\exp[-h(t)t], \tag{9}$$

TABLE 3 Male credentials by race (number of spells = 5037).

	License	Certification	No	Total
White, %	81	68	77	78
Black, %	11	9	14	13
Asian, %	5	15	6	6
Other, %	3	8	3	3

Note: Weighted shares. 2013–2019 from the Survey of Income and Program Participation (SIPP) data.

TABLE 4 Male credentials by education level (number of spells = 5037).

	License	Certification	No	Total
High school dropout, %	6	4	11	10
High school, %	25	44	29	29
Some college, %	19	15	22	21
College and above, %	50	37	38	40

Note: Weighted shares. 2013–2019 from the Survey of Income and Program Participation (SIPP) data.

$$h(t) = \exp\left(\alpha_0 + \alpha_j \sum_{j=1}^{2} \mathrm{Cr}_{ijt} + \gamma_j \sum_{j=1}^{2} \mathrm{Cr} \times \mathrm{Black}_i + \mathrm{UI}_{it} + X'_{it}\beta + \alpha_y + \alpha_{\mathrm{occ}} + \alpha_s\right), \quad (10)$$

where Cr_{ijt} is the jth occupational credential for an individual i in a month prior to finding a job or staying unemployed when panel ends whichever occurs first. In different specifications we test the associations of an occupational credential $j = 1$ defined as either a license or certification or all possible occupational credentials $j = \{1, 2\}$ separately for licenses and certifications.

Black_i is an indicator variable if race is Black for an individual i.

UI_{it} is an indicator variable for receipt of government-provided unemployment compensation payments received in a month prior to finding a job or staying unemployed when panel ends whichever occurs first.

X'_{it} is a matrix of individual controls, that is, age,[19] race, education, immigrant status, interaction terms between credential and races (not Black or White), and an indicator if a person was laid-off in a month prior to finding a job or when the panel ends whichever comes first. Our reference group is non-credentialed Whites. α_y, α_{occ}, and α_s are year, occupation, and state fixed effects respectively.[20]

As in Chetty (2008) we do not control for search intensity assuming that this is part of the hazard ratio. Occupation fixed effects control for reservation wages determined from previous job. To correct for endogeneity that might come from self-selection we employ a two stage Heckman style procedure much like in Cader and Leatherman (2011).[21] For the cases where we

[19]We use age in the selection equation but replace age variable with indicator variables for age below 36; from 36 to 50; and above 51 in the main equation to achieve convergence.

[20]We control for month fixed effects in the main specifications and results are similar.

[21]In our main approach we look at the association between credentials for Blacks and hazard ratios and find that credentials help increase hazard ratios. As a robustness check we run propensity score matching and find negative association between credentials and unemployment duration which confirms survival analysis results.

have only one indicator variable for an occupational credential, we run a first stage probit model on the occupational credential variable using age, race, and immigrant status as independent variables. We obtain an Inverse Mills ratio from the first stage and use it in the second stage duration model as a regressor.[22] For the case where we have several indicator variables for an occupational credential, we use the same two stage procedure with a multinomial probit model in the first stage. One limitation of this approach is that we rely on functional form for identification.

As an additional robustness check, we also performed estimation using propensity score matching (Rosenbaum & Rubin, 1983). Propensity score matching takes into consideration the independent variables that influence whether an individual will receive the treatment. The term "propensity" refers to the probability of a unit receiving treatment based on its covariate values. By grouping units with similar propensity scores into both the treatment and control groups, this confounding is reduced. The propensity score matching approach corroborates that there is a negative association between occupational credential and unemployment duration (see Table 8 below). Although our main results are robust when we use the propensity score matching approach, it is important to acknowledge limitations of this approach as well (Guo et al., 2020; King & Nielsen, 2019).

Finally, for illustrative purposes, we use a non-parametric Kaplan–Meier estimator to graph survivor functions. In general, with censoring the Kaplan–Meier estimator is defined in Equation (11).

$$\widehat{S} = \prod_{j \mid t_j \leq t} \frac{r_j - d_j}{r_j}, \tag{11}$$

where d_j is the number of spells ending at time t_j. r_j is the number of spells at risk at time $t_{j\text{-}} = \sum_{l|l \geq j}(d_l + m_l)$. m_j is the number of spells censored in time $(t_j; t_{j+1})$.

Figures showing these estimates are presented in Appendix A. From Figure A1, we can see that both licenses and certifications are associated with lower probability of survival, that is, unemployment duration but that association dissipates after sixth month confirming negative duration dependence hypothesis commonly found in the literature (Kroft et al., 2013) and thus we restrict our analysis to short-term spells that are not longer than 6 months (see Figure A2).

6 | RESULTS

To further investigate the association between occupational credentials and unemployment durations, we run regressions that estimate Equation (10). Our results are presented in Table 5.

Based on our economic model and the statistical discrimination argument by Blair and Chung (2021), we explore the association between credentials (licenses or certification) and the hazard ratio among Blacks. The first three columns do not control for selection while the last three columns do. If the hazard ratio is greater than 1 then there is shorter survival for that group, that is, shorter unemployment duration. If the hazard ratio is lower than 1 then the survival is longer for that group, that is, unemployment duration is longer.

[22]PSU (ghlfsam) and Stratum (gvarstr) variables were applied, and Taylor Series Linearization was used to produce design-adjusted standard errors.

TABLE 5 Survival analysis results for credentials.

	(1)	(2)	(3)	(4)	(5)	(6)
Credential*Black	1.46***	1.58***	1.42**	1.44**	1.57***	1.40**
	(2.70)	(2.94)	(2.48)	(2.56)	(2.86)	(2.35)
Black	.93	.90	1.02	.83*	.82*	.89
	(−.80)	(−1.27)	(.23)	(−1.70)	(−1.95)	(−1.23)
Credential	1.13**	1.09	1.03	1.14**	1.10*	1.04
	(2.29)	(1.62)	(.55)	(2.46)	(1.72)	(.65)
UI receipt	.79***	.76***	.75***	.79***	.77***	.75***
	(−4.30)	(−5.07)	(−5.00)	(−4.27)	(−5.04)	(−4.94)
Inverse Mills ratio				2.96*	2.32	3.81**
				(1.88)	(1.52)	(2.26)
4-digit occupation FE			Yes			Yes
Year FE		Yes	Yes		Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes
Spells	5073	5073	5073	5073	5073	5073

Note: *t* statistic in parentheses. 2013–2019 from the Survey of Income and Program Participation (SIPP) data. Sample inclusion criteria: males aged 18–65 who enter panel with a job, experience a job loss, and were in a panel for at least 3 months and experience short term unemployment spell no longer than 6 months. (1) Survival model with exponential distribution and state fixed effects; (2) The same as (1) and year fixed effects; (3) The same as (2) and 4-digit occupation fixed effects; (4) The same as specification (1) and controlling for selection using Heckman two step procedure; (5) The same as specification (2) and controlling for selection using Heckman two step procedure; (6) The same as specification (3) and controlling for selection using Heckman two step procedure. Controls include indicator variables for age groups below 35, 36–50, and above 50; race; education; immigrant status; interaction terms between credential and races and an indicator variable if laid-off. Our reference group is non-credentialed whites. All specifications control for the receipt of unemployment insurance. All regressions are weighted by panel sampling weights. PSU (ghlfsam) and Stratum (gvarstr) variables were applied, and Taylor Series Linearization was used to produce design-adjusted standard errors. Strata with single sampling units are treated as certainty unit.

*$p < .10$;

**$p < .05$;

***$p < .01$.

Column (1) of Table 5 presents estimated coefficients from a survival model with an exponential distribution and state fixed effects. Column (2) controls for state and year fixed effects whereas column (3) controls for occupation fixed effects on a 4-digit level, state, and year fixed effects.

Columns (4)–(6) are exactly the same as specifications in columns (1)–(3), respectively, but with accounting for selection using a two-step Heckman procedure. Controls include indicator variables for age groups below 35, 36–50, and above 50; race; education; immigrant status; interaction terms between credential and races (not Black or White) and an indicator variable if laid-off. All specifications control for the receipt of unemployment insurance. All regressions are weighted by panel sampling weights. PSU (ghlfsam) and Stratum (gvarstr) variables were applied, and Taylor Series Linearization was used to produce design-adjusted standard errors. Strata with single sampling units are treated as a certainty unit. Our main variable of interest is the interaction of the credential and Black dummy. We see clear and consistent evidence that occupational credentials among Blacks have a hazard ratio of greater than 1 and thus unemployment duration is shorter for that group if they also possess a credential. We see less consistent and smaller estimates of the effects of credentials on White unemployment duration as evidenced by the credential dummy by itself. Further, the receipt of unemployment benefits expectedly has a hazard ratio that is lower than 1 and thus it is associated with longer unemployment duration.

We now turn our attention to Table 6 where we break down credentials into licenses and certifications. Similar to Table 5, column (1) controls for state fixed effects, column (2) controls for state and year fixed effects whereas column (3) controls for occupation fixed effects on a 4-digit level, state, and year fixed effects. Columns (4)–(6) are the same as specifications in columns (1)–(3), respectively but with accounting for selection using a two-step Heckman procedure. Controls and weights are exactly the same as in Table 5. Our main variables of interest this time are the individual credential types: licenses and certification, each interacted with the Black dummy variable. As you can see from Table 6 the hazard ratios for licenses and certifications among Blacks are both greater than 1 which indicates shorter survival, that is, shorter unemployment duration. Interestingly, the coefficient on the certification*Black interaction term is consistently larger than the coefficient on license*interaction term. We perform a Wald test to see if the two coefficients are statistically different—we find some evidence of this, but it is not consistent across specifications. Conservatively, we can say certification and licensing are both associated with similar reductions in unemployment duration for Black males. Interestingly for White males, only licensing appears to be associated with reductions in unemployment duration.

6.1 | Robustness check

In this section we conduct robustness checks for our results in Table 6 with alternative specifications. First, we use an alternative state fixed effect. Our baseline state fixed effects are based on state of residence for the interview address. Here, we use state of residence in a month when a person found a job or panel ended whichever came first. We do this to control for state specific characteristics where a job was found, or when the panel ended whichever occurred first. Second, we try using a different distribution for our survival model. Next, we further relax assumptions on the distribution and use a Cox proportional hazard model. Fourth, we control for the seam effect which is an attribute of older waves from the SIPP panel data.[23] Next, we check sensitivity of the results to different techniques for variance estimation using complex survey design. Finally, we also run propensity score matching (Rosenbaum & Rubin, 1983) to correct for selection bias and see if our results hold with a different approach. Results are in Tables 7 and 8.

All columns of Table 7 augment specification (6) in Table 6 in one way or another. Column (1) uses state variable for state fixed effects as the state of the residence at the time of finding a job or when the panel ends, and a person is unemployed whichever comes first. Column (2) uses a Weibull survival model as an alternative estimation. Column (3) uses a Cox proportional

[23]When you interview people every 4 months and construct a panel, there are irregularities in the data on the "seam" month, that is, on each 4th month. SIPP used to interview people every 4 months, but now the reference period is 12 months, so when you seam the responses there might be irregularities every 12 months where responses are seamed. We control for this with an indicator variable for the 12th month.

TABLE 6 Survival analysis results for licenses and certification.

	(1)	(2)	(3)	(4)	(5)	(6)
License*Black	1.42**	1.53**	1.39**	1.41**	1.52**	1.36**
	(2.41)	(2.58)	(2.17)	(2.28)	(2.50)	(2.01)
License	1.14**	1.10*	1.05	1.15**	1.11*	1.06
	(2.34)	(1.71)	(.82)	(2.51)	(1.82)	(.98)
Certification*Black	1.99***	2.67***	2.24***	1.84**	2.53***	2.31***
	(2.77)	(4.41)	(3.67)	(2.42)	(4.10)	(3.68)
Certification	1.01	.97	.84	1.02	.97	.82
	(.08)	(−.20)	(−1.33)	(.14)	(−.21)	(−1.43)
Black	.93	.90	1.02	1.04	1.05	1.08
	(−.80)	(−1.28)	(.23)	(.10)	(.13)	(.20)
UI receipt	.79***	.77***	.75***	.79***	.77***	.75***
	(−4.28)	(−5.02)	(−4.97)	(−4.28)	(−5.02)	(−4.91)
License*Black = Cert*Black, *F*-stat	1.54	4.90	3.41	.92	3.92	3.99
Prob > F	.22	.03	.07	.34	.05	.05
4-digit occupation FE			Yes			Yes
Year FE		Yes	Yes		Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes
Spells	5073	5073	5073	5073	5073	5073

Note: *t* statistic in parentheses. 2013–2019 from the Survey of Income and Program Participation (SIPP) data. Sample inclusion criteria: males aged 18–65 who enter panel with a job, experience a job loss, and were in a panel for at least 3 months and experience short term unemployment spell no longer than 6 months. (1) Survival model with exponential distribution and state fixed effects; (2) Specification (1) and year fixed effects; (3) Specification (2) and 4-digit occupation fixed effects; (4)–(6) The same as (1)–(3) but controlling for selection. Controls include indicator variables for age groups below 35, 36–50, and above 50; race; education; immigrant status; interaction terms between credential and races and an indicator variable if laid-off. The reference group is non-credentialed Whites. All specifications control for the receipt of unemployment insurance. Specifications 4–6 include Inverse Mills ratio controlling for selection using Heckman style two step procedure. All regressions are weighted by panel sampling weights. PSU (ghlfsam) and Stratum (gvarstr) variables were applied, and Taylor Series Linearization was used to produce design-adjusted standard errors. Strata with single sampling units are treated as certainty unit.
$^{*}p < .10$;
$^{**}p < .05$;
$^{***}p < .01$.

hazard model—a semiparametric model. Column (4) controls for possible seam bias, that is, an indicator variable for the 12th month (Shaefer, 2013). Seam bias or seam effect was largely alleviated with the 2014 SIPP. Column (5) controls for seam bias and the strata with one sampling unit are centered at the grand mean instead of being treated as a certainty unit. More specifically, this specification changes our approach to variance estimation with complex survey design and it shows that results are not sensitive to the choice the way strata are treated. Column (6) further corroborates robustness of the results to a different approach to handle strata with single observations by reassigning those observations to strata with two or more observations.

Similar to Table 6, we consistently find evidence that the Black*Certification and Black*License coefficients are larger than one and associated with reductions in unemployment

TABLE 7 Survival analysis results for licenses and certification robustness check.

	(1)	(2)	(3)	(4)	(5)	(6)
License*Black	1.33*	1.82**	1.37*	1.28*	1.28*	1.28*
	(1.86)	(2.03)	(1.95)	(1.73)	(1.71)	(1.71)
License	1.07	1.13	1.09	1.08	1.08	1.08
	(1.12)	(1.17)	(1.30)	(1.25)	(1.25)	(1.25)
Certification*Black	2.31***	3.78***	2.10***	2.11***	2.11***	2.11***
	(3.32)	(3.60)	(3.16)	(3.90)	(3.88)	(3.88)
Certification	.84	.72	.87	.78*	.78*	.78*
	(−1.33)	(−1.21)	(−.95)	(−1.88)	(−1.87)	(−1.87)
Black	1.08	1.04	1.08	.99	.99	.99
	(.22)	(.07)	(.19)	(−.02)	(−.02)	(−.02)
UI receipt	.76***	.58***	.73***	.69***	.69***	.69***
	(−4.61)	(−5.27)	(−4.68)	(−6.03)	(−6.03)	(−6.01)
License*Black = Cert*Black, *F*-stat	3.67	2.50	2.28	4.68	4.60	4.64
Prob > F	.06	.11	.13	.03	.03	.03
4-digit occupation FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes
Spells	5073	5073	5073	5073	5073	5073

Note: *t*-statistics in parentheses. 2013–2019 from the Survey of Income and Program Participation (SIPP) data. Sample inclusion criteria: males aged 18–65 who enter panel with a job, experience a job loss, and were in a panel for at least 3 months and experience short term unemployment spell no longer than 6 months. All specifications are the same as specification (6) in Table 6 but (1) uses state of the residence at the time of finding a job for state fixed effects; (2) uses Weibull survival model instead; (3) uses Cox proportional hazard model instead; (3)–(5) control for seam bias and (4) the strata with one sampling unit are centered at the grand mean instead of being treated as certainty unit; (5) strata with singleton observations reassigned to strata with two or more observations. All specifications include Inverse Mills ratio controlling for selection using Heckman style two step procedure. Controls include indicator variables for age groups below 35, 36–50, and above 50; race; education; immigrant status; interaction terms between credential and races and an indicator variable if laid-off. Our reference group is non-credentialed Whites. All regressions are weighted by panel sampling weights. PSU (ghlfsam) and Stratum (gvarstr) variables were applied, and Taylor Series Linearization was used to produce design-adjusted standard errors.
*$p < .10$;
**$p < .05$;
***$p < .01$.

duration. Once more, Wald tests find some evidence that certification is more effective, but the results are not consistent across specifications. Conservatively, we can say that the negative association with each type of credential on black male unemployment duration is similar in magnitude. Results for Whites are less strong with our alternative specification.

As one final robustness check, we perform propensity score matching (Rosenbaum & Rubin, 1983) to correct for selection bias and see if our results hold with a different approach. We match on covariates for race, age, immigrant status, and indicator variable if laid-off. Our dependent variable is unemployment duration. We refer interested readers to Table B2 where we present standardized difference and variance ratios of all independent variables.

TABLE 8 Propensity score matching results for licenses and certification.

	(1)	(2)	(3)
License	−.30***	−.56***	−.56***
	(.000)	(.000)	(.000)
Certification	−.31**	−.50***	−.50***
	(.048)	(.041)	(.038)
Spells	5073	5073	5073

Note: *p*-Value in parentheses. 2013–2019 from the Survey of Income and Program Participation (SIPP) data. Sample inclusion criteria: males aged 18–65 who enter panel with a job, experience a job loss, and were in a panel for at least 3 months and experience short term unemployment spell no longer than 6 months. Our dependent variable is unemployment duration. Specification (1) Propensity score for multivalued treatment with augmented inverse-probability weighting. (2) Propensity score for multivalued treatment for survival analysis with regression adjustment (3) Propensity score for multivalued treatment for survival analysis with inverse-probability-weighted regression adjustment. Observable variables used for matching are indicator for immigrant status, age, and an indicator variable for race. Our main equation controls for indicator variable if laid-off and year fixed effects with robust standard errors.
$^{*}p < .10$; $^{**}p < .05$; $^{***}p < .01$.

Our balance analysis shows that the differences in weighted means are close to zero and the weighted variance is close to one. We don't see that in the raw means and variance, and this confirms that we need to correct for selection bias and the propensity score approach balances the covariates. Results are presented in Table 8.

As we can see from Table 8, both credentials are associated with decreases in unemployment duration and estimates are very similar. Thus, we further corroborate that occupational credentials are associated with reductions in unemployment duration and those reductions are comparable for licenses and certifications.

7 | DISCUSSION

Our paper is a first attempt at uncovering the relationship between occupational regulation and unemployment duration. Our results suggest that both licenses and certifications are associated with a reduction in unemployment duration and those reductions are comparable. We restrict our analysis to Blacks since the economic model results combined with the statistical discrimination argument by Blair and Chung (2021) point out that the association between credentials and spells of unemployment might be more pronounced for that group. We further restrict analysis to males following the approach of Chetty (2008) and Tatsiramos (2009). Tying this empirical approach with our theoretical model suggests that both licenses and certifications provide a signal of ability or increase human capital at similar magnitudes. If anything, certification appears to be more effective than license for Black males, but this difference is not consistent across all specifications.

It is important to note some of the limitations of this study. First, we rely on the functional form for identification in our Heckman two-step estimation—our primary estimations. Thus, our paper is correlational and descriptive and further work should further explore this relationship. It is important to note, however, that our results are robust to different specifications of the state fixed effects, to usage of alternative parametric and semiparametric survival models, controlling for a potential seam effect, as well as different approaches to handling strata with single observations for variance estimation taking care of complex survey design. Finally, our results are robust to using a propensity score matching approach.

A further possible limitation of our paper is that certifications and licenses might be concentrated in different occupations and therefore the results we observe might compare different durations related to those occupation specific labor markets. We control for occupation fixed effects on a 4-digit level, but further studies could investigate particular occupations and compare unemployment spells on a much finer level. Finally, in this study we mainly focus on job finding effects coming from occupational credentials noting that job separation rates might be lower for licensed occupations. Noting that licensing and job-to-job transitions are studied in Kleiner and Xu (2024). As another avenue for further research, we highlight that further studies can focus on decomposing changes in unemployment duration into job finding and job separation effects.

8 | CONCLUSION

This paper introduces a novel extension of a job search and matching model to study the associations between occupational credentials in the form of certifications and licenses and individual unemployment duration. Our model's results are tested in an empirical setting. We find consistent evidence that both licensing and certifications are associated with reductions in unemployment duration for Black males where the statistical discrimination argument by Blair and Chung (2021) is the most pronounced. We find some evidence that certification is associated with a larger reduction, but this difference is not consistent across specifications. Of course, certification is generally less expensive and intrusive than licensing. Thus, certification may provide just as effective of a signal (or human capital improvement) for Black males and thus may be associated with shorter unemployment durations.

As policy makers across the world reevaluate the costs and benefits of occupational licensing, our results indicate that certifications at worst may provide similar human capital improvements and/or signaling for Black job seekers. There is some evidence that the signal/human capital effect is stronger for certification relative to licensing. Workers also have a choice when considering whether to acquire certification, but with licensing the decision is mandated by law. Certification may provide a more efficient mechanism for Black males to improve human capital as well as signal ability without the associated costs of mandated licensing.

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APPENDIX A

Kaplan–Meier estimates for individual occupational credentials as well as for different occupational credentials are presented in Figures A1 and A2.

The lines in Figure A1 represent survival estimates. The lower the line the lower the probability of surviving in the next period, that is, staying unemployed in the next period, the lower the better for escaping the state of unemployment.

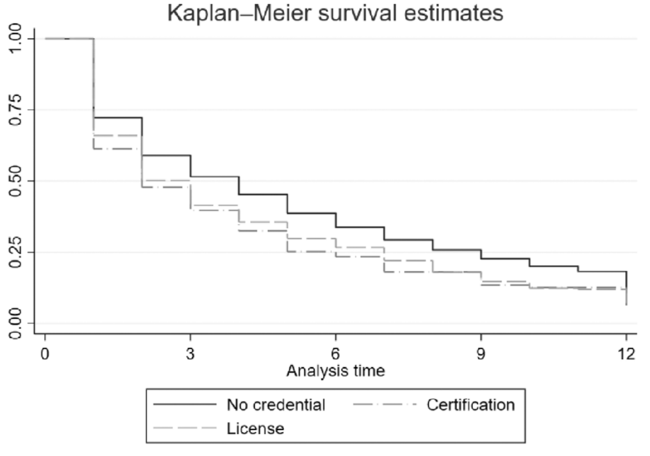

FIGURE A1 Kaplan–Meier estimates by occupational credential.

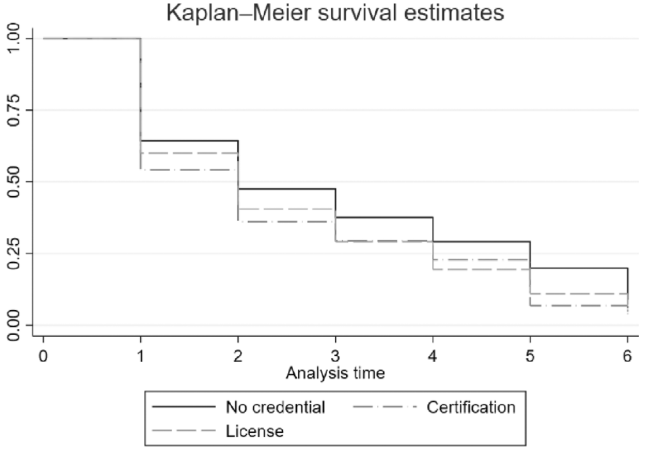

FIGURE A2 Kaplan–Meier estimates by occupational credentials short-term spells.

APPENDIX B

TABLE B1 Summary statistics for independent variables used in the analysis.

	Mean	SD	Min	Max
Indicator if an individual is not a citizen of the United States	.09	.29	0	1
Indicator for whether the individual reported spending some time on layoff for a no-job spell	.15	.35	0	1
Indicator if age is below 36 years	.52	.50	0	1
Indicator if age is from 36 to 50 years	.26	.44	0	1
Indicator if an individual considers herself/himself to be White alone	.79	.40	0	1
Indicator if an individual considers herself/himself to be Black alone	.11	.32	0	1
Indicator if an individual considers herself/himself to be Asian alone	.05	.22	0	1
Indicator if an individual considers herself/himself to be Other than White, Black, or Asian alone	.04	.19	0	1
Indicator if an individual is a high school dropout	.11	.32	0	1
Indicator if an individual's highest level of school is at most high school	.33	.47	0	1
Indicator if an individual has some college credit but no degree	.21	.42	0	1
Indicator if an individual has a college degree and above	.35	.48	0	1

Note: 2013–2019 from the Survey of Income and Program Participation (SIPP) data. Unweighted means.

TABLE B2 Balance analysis for specification (1) in Table 8.

	Standardized differences		Variance ratio	
	Raw	Weighted	Raw	Weighted
License				
Indicator if an individual is not a citizen of the United States	−.219	−.010	.456	.973
Age as of last birthday	.341	.041	.946	.838
Indicator if an individual considers herself/himself to be White alone	.047	−.009	.931	1.014
Indicator if an individual considers herself/himself to be Black alone	−.004	.018	.991	1.043
Indicator if an individual considers herself/himself to be Asian alone	−.094	.004	.651	1.015
Certification				
Indicator if an individual is not a citizen of the United States	.067	.019	1.199	1.056
Age as of last birthday	.185	.027	.877	.802
Indicator if an individual considers herself/himself to be White alone	.068	−.002	.907	1.003
Indicator if an individual considers herself/himself to be Black alone	.047	.000	1.130	1.001
Indicator if an individual considers herself/himself to be Asian alone	−.151	−.000	.469	.999
Spells	5073	5073	5073	5073