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Certifiably employable?: The effects of occupational regulation on unemployment duration

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Abstract

Occupational regulation is a labor market institution that has received a growing amount of attention by researchers. Existing research has explored the effects of occupational regulation on wages and employment. To the best of our knowledge, no existing study has estimated the effect of occupational credentials on unemployment duration in the US. We derive a random search model to explain differences in individual unemployment duration resulting from heterogeneous effects from licenses and certificates. Our model predicts that an occupational credential with a stronger signaling or human capital effect results in a shorter individual unemployment duration. To estimate the effect of occupational credentials, we use data from the Survey of Income and Program Participation (SIPP) for 2013-2019. We find that individual unemployment duration decreases on average by 3 to 9 days if an individual has a license. In contrast, certificates issued by businesses reduce individual unemployment duration by 24 to 27 days. Our results suggest that certificates issued by businesses contain stronger signals and human capital improvements than government issued licenses.

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1 Introduction

More than 20% of workers in the United States have an occupational license (Kleiner and Krueger 2013; Cunningham 2019). On average it has been estimated that 22% of workers in the European Union are also licensed (Koumenta and Pagliero 2019). In the US 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 US held either a professional license or a certificate (Cunningham 2019).

Theoretically, occupational licensing is viewed as a form of rent-seeking (Friedman and Kuznets 1945; Friedman 1962) 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 (1973) 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 result in 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 and Carpenter 2016). Certification, a less restrictive form of occupational regulation, often prevents workers from using job titles (for example, certified hairdresser).

First, we 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. In addition, we use a propensity score matching estimation as an additional check for robustness.

Our results suggest that there are heterogeneous effects of different forms of occupational credentials on individual unemployment duration. More specifically, we find that having a license decreases unemployment duration by 3 to 9 days while certificates issued by businesses reduce unemployment duration by 24 to 27 days on average. We find less consistent evidence that other types of credentials are also reducing unemployment duration. We also find evidence that the effect varies for different groups of workers. Our search model suggests that the empirical findings correlate with the strength of the effect of each credential. In particular, the human capital and signaling effects of certificates issued by businesses are stronger than those of licenses after adjusting for the relative distributions of reservation wages between licensed and certified occupations.

Our paper contributes to several strands of literature. First, this paper is the first attempt to examine the effects of occupational credentials on 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 theoretical random search model of job search with occupational credentials. Section 4 contains data analysis and our empirical findings. We conclude our paper in Section 5 and discuss avenues for further research.

2 Literature Review

Many studies have examined the possible causes of unemployment duration in the existing literature. For example, there are studies that have investigated the relationship between unemployment duration and time (Blanckard and Diamond 1994), education (Kettunen 1997), labor force attachment (Abraham and Shimmer 2001), unemployment benefits and business cycle (Bover et. al. 2002; Røed and Zhang 2002; Lalive 2008), race (Dawkins et. al. 2005), residential location (D´etang-Dessendre and Gaign´e 2009), and personality traits (Uysal and Pohlemeier 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 US 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 and 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 US and Europe (Nunn, 2016) whereas others like animal breeders and art therapists are licensed in only a few states (Carpenter et. al. 2017; Knee CSOR database, 2022). Thus, licensing requirements while being mandatory vary significantly from state to state as well as the city level in some cases (Hall et al. 2019; Deyo et al. 2021). For an example of public members on the licensing boards see Grady 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.[3] Some studies have focused on particular occupations and estimated wage premiums for licensed barbers (Timmons and Thornton 2010), lawyers (Pagliero 2010), massage therapists (Thornton and Timmons 2013), opticians (Timmons and Mills 2018), radiologic technologists (Timmons and 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 US (Kleiner and Krueger 2010 and 2013; Ingram 2019; Gittleman, Klee, and Kleiner 2018; Gittleman and Kleiner 2015). Recent work suggests that the effects of licensing may take some time to be realized in the labor market due to grandfather provisions (Han and Kleiner 2021). Licensing is also found to reduce labor supply by 17 to 27 percent (Blair and Chung 2019), increase education time, increase wages, reduce employment, and overall decrease welfare (Kleiner and Soltas forthcoming).

[3] Perhaps owing to the paucity of de-licensing (Thornton and Timmons 2015; Thornton, Timmons and Kukaev 2021), considerably less is known about the effects of removing occupational licensing (Pizzola and Tabarrok 2017; Timmons and Thornton 2019).

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 percent (Koumenta and Pagliero 2019). For China, wages increase by 15 percent as a result of licensing (Chi, Kleiner, and Qian 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, Carrol and 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 US reduced maternal mortality by 7 to 8 percent (Anderson et al 2020)[4]. More recent licensing of electricians had no effect on injuries and death rates among electricians (Kleiner and 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 percent less likely to switch occupations and 3 percent less likely to become unemployed the following year (Kleiner and Xu 2020) while overall increasing allocation of talent to tasks (Qui 2020). Finally, licensing also affects entrance exam difficulty (Pagliero 2013) as well as

[4] For earlier discussion on midwifery licensing see Adams et al. 2003.

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 effects of occupational credentials on unemployment duration. We begin by developing a random search model that derives conditions for heterogeneous effects of occupational credentials on individual unemployment duration. We then test the results of our model using an exponential survival analysis. As robustness exercises, we restrict the subsample using different criteria i.e., removing youth and long-term unemployed, focusing on minority subsamples, imperfectly controlling for occupation fixed effects as well as running a propensity score matching estimators. Results hold.

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 creates 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. [5] Following Mortensen (1977), we define the escape rate as the probability that an offer arrives multiplied by the probability that the offer is acceptable i.e., the transition into the new state of a newly accepted job. Unemployment duration is inversely related to the escape rate. Heterogeneity in the effects of licensing and certification on unemployment duration arises from differences in expected frequencies with which workers find acceptable offers.

Assume a time interval h and that the share of time devoted to search is s. Search intensities can capture different search efforts as well as different search technologies i.e. formal search through job centers vs informal search through employed friends and the Internet. Let α be defined as a positive parameter that indicates that the probability of escaping unemployment is proportional to the time devoted to search: αsh. That is, the probability that an offer will arrive.

The parameter α can be thought of as 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 i.e. 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 of these characteristics can be captured by α. In other words, αsh denotes the probability that an offer arrives from a prospective employer during interval h.[6]

[5] A more complete description of the model can be found in Appendix A.

[6] As an example, assume that time interval is a day i.e. h=1 and half of the day is spent on search. Then s = 0.5. If α = 0.5, then probability that an offer arrives is 0.25. If there is an increase in vacancies and job market is tighter α can rise to for example α = 0.6, then probability that an offer arrives is 0.3.

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, $F(w) > 0$. We can then define the escape rate (q) as the product of the probability that an offer arrives from a prospective employer during interval h i.e. αsh and the probability $[1 - F(w)]$ that the offer is acceptable to the individual job seeker. As a result, the probability that a worker makes a transition from unemployment to employment in time interval h is hq and that probability varies with search efforts as well as occupational credentials.

Assume that people with licenses search for jobs with a search intensity s_1 while people with certificates search for jobs with a search intensity s_2. Different search intensities could be a result of heterogeneity in reservation wages among individuals with various occupational credentials or a result of different preferences for leisure. In our model, escape rates are also influenced by heterogeneity in the human capital improvement/signaling strength of our two types of occupational regulation, licenses, and certificates. Licensed individuals have access to a set of occupations that is captured by α_1 while certified individuals have access to another set of occupations captured by α_2. The strength of a signal is denoted as μ. The source for a market signal can be viewed as a cost associated with investment in licensing as in Spence (1973) 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).

The strength of the signals that licenses and certificates send to prospective employers can be different. The combination of the access to different occupations and a job market signal is $\alpha_1\ \mu_1$ for licensed individuals and $\alpha_2\ \mu_2$ for certified individuals. Thus, the main conclusion of the proposed model that follows below is that unemployment duration is expected to be shorter for occupational credentials that have stronger human capital or signaling effects. The type of occupational regulation, licensing or certification, that has a stronger effect remains a testable empirical question.

In our proposed model, search is random. More specifically, wage offers arrive as a random draw from the known distribution $F(w)$. A key difference from Mortensen (1977) arises from the fact that we model two regulatory regimes: licensing and certification. Thus, there are two wage-offer distributions $F_1(w)$ for licenses and $F_2(w)$ for certificates. Let us introduce the following assumption.

Assumption 1. *Since licensing increases wages in licensed occupations and certification is a less strict regime, 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 $F_2(w)$.*[7]

If $\overline{w}_1$ and $\overline{w}_2$ are maximum attainable wages under licensing and certification, then $\overline{w}_1 > \overline{w}_2$ and $F_1(\overline{w}_1) = 1$ as well as $F_2(\overline{w}_2) = 1$. To the best of our knowledge, there is no study that directly tests assumption 1. However, papers by Kleiner and Krueger (2013) for the US as well as Koumenta et al. (2022) for Europe indirectly support assumption 1 by providing

[7] Thus $F_1(w) \leq F_2(w) \Longrightarrow 1 - F_1(w) \geq 1 - F_2(w)$.

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.[8]

The escape rate is the expected frequency with which workers find acceptable offers. The escape rate is the product of the probability that an offer arrives during interval h and the probability that the offer is acceptable. The probability that a worker makes a transition from unemployment to employment in interval h is hq, and we can define escape rates as follows

$$q_1 = \alpha_1 s_1 [1 - F_1(w)] \mu_1 \textit{ if licensed} \tag{1}$$

$$q_2 = \alpha_2 s_2 [1 - F_2(w)] \mu_2 \textit{ if certified} \tag{2}$$

Following assumption 1, escape rates will be greater for credentials having stronger human capital and signaling effects adjusting for relative reservation wages and search efforts:

$$q_1 > q_2 \quad \textit{if} \quad \alpha_1 \mu_1 > \alpha_2 \mu_2 \frac{[1-F_2(w)]s_2}{[1-F_1(w)]s_1} \tag{3}$$

Otherwise,

$$q_2 > q_1 \quad \textit{if} \quad \alpha_2 \mu_2 > \alpha_1 \mu_1 \frac{[1-F_1(w)]s_1}{[1-F_2(w)]s_2} \tag{4}$$

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

[8] Reservation wages decline with unemployment duration (Kiefer and Neumann 1979). Reservation wages are also affected by observable (Prasad 2003) and unobservable characteristics (McGee 2014, Caliendo et al 2015).

and one where a worker is qualified. We will consider the case where a worker is not qualified for unemployment benefits. 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

$$D_i^0 = \int_0^\infty v q_i^0 exp^{-q_i^0 v} dv = 1/_{q_i^0} \quad (5)$$

Here, the augmented model allows us to compare the heterogeneous effects of licensing and certification on duration through escape rate q_i^0 where i stands for occupational credential. Thus, duration of workers who have a license is shorter than the duration of workers who have a certificate if

$$D_1^0 < D_2^0 \ \ if \ \ 1/_{q_1^0} < 1/_{q_2^0} \rightarrow q_1^0 > q_2^0 \quad (6)$$

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). More details can be found in Appendix A. Graphically these results are presented in Figure 1. As shown in Figure 1, v is the length of the spell of unemployment duration. q_i^0 denotes the escape rate for individuals without unemployment benefits and i = 1,2 denotes an individual who has a license or a certificate respectively. Panel (a) illustrates when individuals with licensing have an easier time finding a job and vice versa for panel (b).

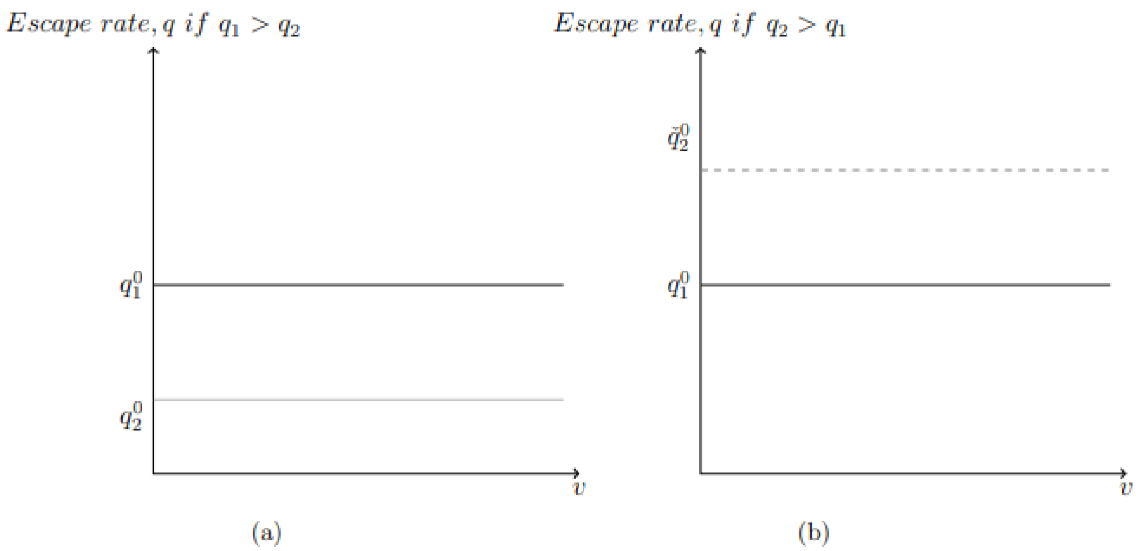

Figure 1: Comparison of relationship between escape rates and duration of unemployment between licensing and certification. Note: q_1 is licensing and denoted with a solid line; q_2 is certification and denoted with a dashed line.

4 Data analysis

a) Sample selection and summary statistics

In this section we describe our dataset and how we constructed our subsample. We also describe how we construct unemployment duration and our occupational credentials variables. To test the strength of licenses and certificates, we use the Survey of Income and Program Participation (SIPP) data base for the time period of 2013-2019 in the US.[9] The SIPP is a nationally representative panel data set on employment, income, and program participation dynamics. Most importantly for the purpose of our analysis, the survey asks participants whether they earned a professional certification or license. Previous research has utilized the SIPP to examine the effects of licensing on wages and employment (Blair and

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

Chung 2022 and Gittleman et al. 2018). We should further note that the SIPP dataset 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 look at 2013 to 2019 since it doesn't contain any lagging effects from the financial crisis of 2008, nor does it contain any abnormalities in unemployment duration due to the COVID-19 pandemic. Further, 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 observations, but we focus on a subsample of 125,747 observations of unemployed individuals for our analysis. The subsample criteria are as follows. First, we focus on people who have experienced unemployment. Second, we focus on prime aged workers between 18 to 65. Most of our sample has no reported wage for their first job. Nonetheless, we restrict the sample to wages below $200K a year to exclude wage outliers (see summary statistics in Table 9 Appendix C). Further, we combine the household sample unit identifier[10] and a person number identifier[11] to create an individual specific identifier variable.

Duration is measured in months. For the purposes of our analysis, we focus our attention on the first observed unemployment spell. We use the beginning and ending months of looking for work to construct the duration variable.[12] The dataset does not contain incomplete durations. More specifically, duration of unemployment is constructed as the

[10] Denoted as ssuid in the SIPP
[11] Denoted as pnum in the SIPP
[12] Denoted as enj_flkmn1 in the SIPP

difference between the ending month of the first unemployment spell and the beginning month of the unemployment spell plus one.[13] The SIPP dataset does not contain incomplete duration for the first unemployment spell and thus our sample contains individuals who have completed duration of the first unemployment spell only. We should note that our model in Appendix A is general and allows for both employed and unemployed search, but limitations in the SIPP data require that we focus solely on unemployed search in the empirical section.

Occupational credential variables are constructed as follows. We construct four indicator variables: licenses, certificates issued by a business or a company, certificates issued by professional or trade associations, and other certificates issued by other groups or organizations.[14] The variable "license" is defined as a credential awarded by a governmental licensing agency on the basis of a predetermined criteria — e.g., degree attainment, certifications, assessment, apprenticeship programs, or work experience. This definition is consistent with the previous literature (Allard, 2016; Gittleman et. al. 2018; Kukaev et. al. 2020; Blair and Chung 2022).

Before turning to our subsample analysis, some observations are in order. Occupational credentials will matter for unemployed individuals only if we observe people with licenses and certificates becoming unemployed. In the full SIPP sample, the share of people without an occupational credential is 83.12 percent; 11.46 percent with a license; 4.31 percent with

[13] As an illustrative example, if the beginning of the month of the spell is February and ending month of the spell is May, then the beginning month is equal to two and the ending month equals five. Thus, the spell is 5-2+1 = 4 months.

[14] Those correspond to variables ewhocert1, ewhocert2, ewhocert3, and ewhocert4 in the SIPP. We differentiate between certificates issued by companies, associations, and other organizations to see the effects of certification by various institutions.

a certificate issued by an association; 0.55 percent with a certificate issued by another organization, and 0.56 percent have a certificate issued by businesses. In the subsample of individuals who are unemployed—our main subsample of interest, 84.36 percent do not have an occupational credential; 9.41 percent have a license; 4.59 percent have a certificate issued by an association; 0.91 percent have a certificate issued by other organization while 0.73 percent have a certificate issued by a business. In short, the attainment of licenses and certification is similar for the full sample and unemployed subsample. Licensing attainment is slightly lower among the unemployed and slightly higher for all types of certification.

Descriptive statistics for our sample are presented below. Duration is measured in months. Table 1 Panel A shows the unconditional unemployment duration by gender. Unconditional unemployment duration by race is presented in Table 1 Panel B. The shares of the population by educational attainment level are presented in Table 1 Panel C.

Table 1 Panel A: Unemployment duration by gender

Characteristic	%	Duration (St.Dev.)
Male	52	7.90(3.80)
Female	48	7.36(3.82)

N= 125,747

Table 1 Panel B: Unemployment duration by race.

Characteristic	%	Duration (St.Dev.)
White	68	7.50 (3.83)
Black	22	8.07 (3.76)
Asian	4	7.57(3.86)
Residual	6	7.73 (3.82)

N = 125,747

Table 1 Panel C: Unemployment duration by educational attainment.

Characteristic	%	Duration (St.Dev.)
High School	52	8.02 (3.80)
Some College	23	7.34 (3.87)
College and above	25	7.12 (3.74)

N = 125,747

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

As shown in Table 1 Panel A, our sample is 52 percent male and 48 percent female. Unconditional unemployment duration is shorter in the female subsample. Table 1 Panel B shows that most of the sample population is white, and the second dominant group is black. The unconditional unemployment spell is longest for the black subsample and the shortest for the white subsample. Turning to Table 1 Panel C, slightly more than half of the sample of unemployed people has attained a high school degree. Education seems to be negatively correlated with unemployment duration in our sample.

Table 2 summarizes average unemployment duration for the four different types of occupational regulation credentials.

Table 2: Unemployment duration for different occupational credentials

	License	Certificate (business)	Certificate (association)	Certificate (other)	None	Total
U duration, months	6.97	6.79	7.30	7.61	7.74	7.64
(St.Dev.)	(3.76)	(3.85)	(3.72)	(3.98)	(3.82)	(3.82)
Observations (NT)	11,831	918	5,766	1,147	106,085	125,747

N = 125,747

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

As we show in Table 2, workers with licenses and certificates have shorter unemployment durations than individuals without occupational credentials. The shortest unemployment duration, on average, is observed for individuals with certificates issued by businesses or companies. Two examples of this type of certificate are project manager certificates or information technology certificates.

A further breakdown by individual characteristics for each credential group is shown in Table 3. Panel A shows a comparison by gender. Panel B shows a breakdown of the sample by race.

Table 3: Panel A Credentials by gender

	License	Certificate (business)	Certificate (association)	Certificate (other)	No	Total
Male, %	44.90	74.84	47.23	56.23	52.37	51.63
Female, %	55.10	25.16	52.77	43.77	47.63	48.37

N = 125,747

Table 3: Panel B Credentials by race

	License	Certificate (business)	Certificate (association)	Certificate (other)	No	Total
White, %	71.75	61.22	65.80	65.39	67.55	67.80
Black, %	18.99	26.58	22.81	24.32	22.02	21.83
Asian, %	4.16	5.56	4.79	5.23	4.64	4.62
Residual, %	5.10	6.64	6.61	5.06	5.79	5.76

N = 125,747

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

As you can see from Table 3 Panel A, males are overrepresented in the business certificate sample and slightly overrepresented in the certificate (other) category. On the other hand, females are slightly overrepresented in the licensed category.

Table 4: Credentials by education level

	License	Certificate (business)	Certificate (association)	Certificate (other)	No	Total
High school	29.85	43.36	28.25	37.05	55.87	51.89
Some college	26.96	24.51	26.12	28.16	22.16	22.86
College and above	44.18	33.14	45.63	34.79	21.97	25.24

N= 125,747

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

Turning our attention to Table 3 Panel B, the share of whites is largest in the licensing sample. Interestingly, for certificates the share of whites is lower than the overall share of whites in the sample. The share of blacks is the largest for certificates issued by businesses as well.

Table 4 contains comparisons for each credential group by education. Table 4 highlights that the unemployed who have a license or a certificate issued by an association are more educated, while most people who don't have any occupational credentials among the unemployed sample have a high school education.

Next, we examine the most common occupations by credential in both the full SIPP sample and our unemployed sample used for empirical analysis. Table 5 Panels A and B provides this information for both the full SIPP sample and our unemployed sample, respectively.

Table 5 Panel A: Major occupation by credentials full sample, % of observations

Credential	Major occupation	%	N
License	Elementary and middle school teachers	6.05	524,350
Certificate (business)	Industrial truck and tractor operators	1.97	29,887
Certificate (association)	Registered nurses	4.79	229,939
Certificate (other)	Clergy	4.53	27,444

N = 4,575,305

Table 5 Panel B: Major occupation by credentials full sample, % of observations

Credential	Major occupation	%	N
License	Driver/sales workers and truck drivers	0.36	11,831
Certificate (business)	Computer support specialists	0.65	1,069
Certificate (association)	Registered nurses	0.25	6,362
Certificate (other)	Medical assistants	0.24	1,234

N = 125,747

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

For the full SIPP sample of 4,575,305 observations, 43.7 percent reported their occupations. If we focus on our subsample of 125,747 individuals that experienced unemployment, only 5.05 percent reported their occupations. For the full SIPP sample, the most common licensed occupation is elementary and middle school teachers. Turning to certificates, industrial truck and tractor operators, registered nurses, and clergy are the most common occupations for business, association, and all other types of certification respectively. Table 5 Panel B present major occupations for the unemployed subsample. For unemployed individuals with licenses the most common occupation is driver/sales workers and truck drivers. For people with certificates issued by businesses, the most common occupation is computer support specialists. Finally, for certificates issued by associations and other organizations, the most common occupation is registered nurses and medical assistants respectively. As we shall note further later, the low number of unemployed respondents reporting occupation limits what we can draw from this comparison. It should be noted that registered nurses are the most common occupation for respondents with association certificates in both samples.

b) Data analysis

Equations (11) and (12) represent our econometric model. For the survival analysis, the survivor and hazard functions have the following forms.

$$S(t) = exp[-exp(h(t))t] \quad (11)$$

$$h(t) = \exp(\alpha_0 + \alpha_j \sum_{j=1}^{4} Credential_{ijt} + UI_{it} + X_{it}'\beta + \alpha_y + \alpha_m + \alpha_s) \quad (12)$$

where

$Credential_{ij}$ is the j^{th} occupational credential for an individual i. In different specifications we test the effects of a single occupational credential j = 1 or all possible occupational credentials j = {1,4}.

UI_{it} is an amount of regular, government-provided Unemployment Compensation payments received in each month of reference period.

X'_{it} is a matrix of individual specific controls i.e. age, age squared[15], gender, race, education, immigrant status, if a person was laid-off, and a set of six indicator variables for search intensity. Our indicator variables for search intensity include: 1) if an individual attended any classes to improve basic reading or math skills; 2) if an individual attended any job readiness training to learn about resume writing, job interviewing, or building self-esteem; 3) if an individual attended any job search program or job clubs, or use any job resource centers to find out about jobs, to schedule interviews, or to fill out applications; 4) if an individual attended any training to learn specific job skills, such as computers, car repair, nursing, day care work, or some other job skills; 5) if an individual attended training or used job resources because it was required, a choice, or both; and 6) if an individual participated in a work experience program in exchange for Temporary Assistance for Needy Families (TANF).

α_y, α_m, and α_s are year, month, and state fixed effects respectively.

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).[16] For the cases where we have only one indicator variable for an occupational credential, we run a first stage probit model on the occupational credential variable using gender, race, age, and age squared as independent variables. We obtain an Inverse Mills ratio from the first stage and use it in the

[15] When we estimate effects of each occupational credential separately, we use age and age squared. However, when we look at all occupational credentials together, we use those in the selection equation but replace age variable with indicator variables for age below 36; from 36-50; and above 51 in the main equation to achieve convergence. Robustness check exercises show that results are similar to these alternative specifications.
[16] Comparing our results with results from propensity score matching, results from the latter are similar but effects are slightly bigger (See Tables 7 and 8).

second stage duration model as a regressor.[17] 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 and 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. Results from our main approach are similar direction-wise but slightly smaller in magnitude than when we use propensity score matching (see Tables 8 and 9 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 (King and Nielsen 2019, Guo et al 2020).

Finally, for illustrative purposes, we use a non-parametric Kaplan-Meier estimator to graph survivor functions. In general, with censoring[18] the Kaplan-Meier estimator is defined in equation 13.

$$\hat{S} = \prod_{j \mid t_j \leq t} \frac{r_j - d_j}{r_j} \tag{13}$$

[17] We use bootstrapped standard errors with 50 repetitions and seed 10101 in STATA for the two stage procedure.

[18] When there is no censoring, the most straightforward estimator of the survivor function is obtained by subtracting the sample cumulative distribution function from one. In this case, the survivor function at time *t*, *S(t)*, is equal to the ratio of the number of spells in the sample that last longer than *t* to the total sample size, *N*.

d_j is the number of spells ending at time t_j

r_j is the number of spells at risk at time $t_{j-} = \sum_{l \mid l \geq j} (d_l + m_l)$

m_j is the number of spells censored in time $[\, t_j \,; t_{j+1} \,)$

Figures showing these estimates are presented in Appendix B

4.1 Results

To further investigate the effect of occupational credentials on unemployment durations, we run regressions that estimate equation 11. For our first set of estimations, we explore the effect of each type of credential (licenses and the three types of certificates) separately. Our results are presented in Table 6. Estimated coefficients presented in Table 6 are marginal effects where standard errors are computed using the delta method (Cameron and Trivedi 2005, page 231). Each odd numbered column in the table (1, 3, and 5) does not control for selection whereas even numbered columns do control for selection as explained in the preceding section.

Table 6: Survival analysis results using exponential model

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
License	-.317***	-.320***						
	(.063)	(.057)						
Certificate (business)			-0.713***	-0.708***				
			(0.209)	(0.209)				
Certificate (association)					-.045	-.045		
					(.077)	(.077)		
Certificate (other)							.616**	.617**
							(.216)	(.216)
N	125,747	125,747	125,747	125,747	125,747	125,747	125,747	125,747

Standard errors in parentheses

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

Note: 2013-2019 from the Survey of Income and Program Participation (SIPP) data. Our dependent variables defined in eq. 11. Estimates are marginal effects with standard errors obtained using the delta method. Odd specifications do not control for selection while even specifications do control for selection. Controls include Inverse Mills ratios for occupational credentials, state, year, and month fixed effects as well as demographic characteristics including gender, age, age squared, race, education, immigrant status, search intensities variables, amount of unemployment benefits; and an indicator variable if laid-off.

As shown in Table 6, two categories of occupational credentials decrease unemployment duration. Since duration is measured in months, the marginal effect can be converted into days by multiplying the estimated coefficient by the 30 days in a month. As an example, if we multiply our estimated coefficient on licensing by 30 in Table 6, we find that licenses decrease duration by 10 days. We can arrive at the conclusion that certificates issued by businesses decrease unemployment duration by 21 days using a similar calculation. Although the sign on certificates issued by associations is negative, it is not statistically significant. The coefficient on certificate (other) was large and positive and not consistent with our hypothesis. As we shall illustrate soon, the sign on this category of certificates depends upon our specification and we are therefore hesitant to provide an interpretation for this estimate.

Table 7: Survival analysis results using exponential model for all credentials

	(1)	(2)	(3)	(4)	(5)
License	-.31***	-.31***	-.12***	.09	-.58***
	(.06)	(.06)	(.05)	(.20)	(.07)
Certificate(business)	-.82***	-.91***	-.81***	-3.02***	-.50
	(.22)	(.22)	(.13)	(.61)	(.54)
Certificate (association)	-.04	-.07	.08**	-1.12***	-.27**
	(.08)	(.07)	(.04)	(.20)	(.11)
Certificate (other)	.77***	.97***	-.18	2.06	-1.21
	(.23)	(.24)	(.30)	(2.17)	(.81)
N	125,747	125,747	36,932	27,445	60,820

Standard errors in parentheses

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

Note: 2013-2019 from the Survey of Income and Program Participation (SIPP) data. Our dependent variable is defined in eq. 11. Estimates are marginal effects with standard errors obtained using delta method. Main results (1) no selection (2) accounting for selection (3) selection without youth and long term unemployed (4) All black sample with selection and (5) All female sample with selection. Controls include Inverse Mills ratios for occupational credentials; state, year, and month fixed effects as well as demographic characteristics including gender; indicator variables for age groups below 35, 36-50, and above 50; race; education; immigrant status; search intensities variables; amount of unemployment benefits; and an indicator variable if laid-off.

We now turn our attention to our preferred specification where we include controls for all four types of occupational credentials simultaneously. Table 7 presents this set of results. Column 1 of Table 7 displays our results without accounting for selection. Column 2 accounts for selection using a two-step Heckman procedure.

In this first set of results, we see that licensing reduces unemployment duration by 9 days whereas certificates issued by companies reduces duration by 27 days. These are our upper bounds of our estimated coefficients.[19] In these first two estimations, we continue to observe a positive sign on certificate (other). In columns 3 to 5, we make some modifications to our sample to better understand the effect of occupational credentials on unemployment duration. In column 3, we re-estimate our equation excluding workers who are younger than 25 years old and workers with an unemployment duration that is longer than six months. We suspect that credentials might be less helpful for this subset of workers—young workers lack relevant job experience and the long term unemployed may experience depreciation in their acquired human capital. Credentials may be less helpful for this group to signal ability or to build/restore human capital. Our estimates here are mostly consistent with our expectations. The size of the coefficient on licensing is reduced by one-third. The coefficient on certificate (association) becomes significant and positive, but is not economically significant. The coefficient on certification (other) loses significance and switches signs in this estimation. Interestingly, the coefficient on certificate (business) does not change much in this subsample. A relatively small number of young and long term unemployed workers obtain business certificates. In other words, eliminating the young and long term unemployed does not substantially change the size of this subgroup and we suspect this is why do not observe much change in the coefficient.

Conceivably, the effects of occupational credentials on unemployment duration might be stronger for blacks and females. Indeed, previous research by Blair and Chung (2022) finds that the signaling function for licensing is strongest for black men. Columns (4) and (5) of

[19] We find similar results if we exclude all individuals who reported wages for the first job as well as if we estimate our results using and indicator variables for age in the selection equations.

Table 7 present results for the sub-sample of blacks and females, respectively. Interestingly, for blacks, we find no evidence that licensing reduces unemployment duration. We find very large effects, however, for reductions in unemployment duration for blacks from certificates issued by businesses as well as certifications issued by associations. Turning to the effects for women, we once more find evidence that licensing reduces unemployment duration. It would appear that licenses are more beneficial in terms of shortening unemployment spells for women than for men. Also, the sign on business certificates becomes smaller and loses significance. Further, certificates issued by companies are a more useful signaling device or result in more improvements in human capital for males relative to females.

4.2 Robustness check

In this section we conduct a robustness check exercise using propensity score matching (Rosenbaum and Rubin, 1983) to also correct for selection bias and see if our results hold with a different approach. Our first set of results are presented in Table 8. First, we look at each individual occupational credential—similar to our previous Table 6.

Table 8: Effects of occupational credentials on unemployment duration separately.

	(1)	(2)	(3)	(4)
License	-1.11***			
	(.03)			
Certificate (business)		-1.74***		
		(0.04)		
Certificate (association)			-.85***	
			(.04)	
Certificate (other)				-1.23**
				(.05)
N	125,747	125,747	125,747	125,747

Standard errors in parentheses

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

Note: 2013-2019 from the Survey of Income and Program Participation (SIPP) data. Our dependent variable is unemployment duration. Propensity score matching estimation using probit and robust standard errors. Observable variables used for matching are indicator for immigrant status, age, age squared, indicator variable for race and gender.

As shown in Table 8, we obtain similar results direction-wise, but slightly larger in magnitudes. Similar to our previous estimations where we generally found that certification was more effective than licensing at reducing unemployment duration, we continue to find similar results using propensity score matching. It is worth noting that here we also see evidence that both other types of credentials—those issued by associations and other organizations—are also more effective than licensing in this estimation. Since we don't see a consistent result direction-wise using both estimation strategies for certificates issued by associations and other organizations, we believe our results for business credentials are the most credible.

Table 9: Effects of occupational credentials on unemployment duration altogether.

	(1)	(2)	(3)	(4)	(5)
License	-.93***	-.86***	-.88***	-.57***	-.82***
	(.04)	(0.04)	(0.04)	(0.09)	(0.05)
Certificate(business)	-1.34***	-1.27***	-1.25***	-1.77***	-2.38***
	(.15)	(.14)	(.15)	(.37)	(.18)
Certificate (association)	-.60***	-.53***	-.57***	-.75***	-.50***
	(.05)	(.05)	(.05)	(.10)	(.07)
Certificate (other)	-.50***	-.40***	-.40***	-.39**	-1.16***
	(.11)	(.11)	(.11)	(.19)	(.16)
N	125,747	125,747	125,747	27,445	60,820

Note: 2013-2019 from the Survey of Income and Program Participation (SIPP) data. Our dependent variable is unemployment duration. Specification (1) is propensity score matching estimation multivalued treatment with inverse probability weighting. Observable variables used for matching are indicator for immigrant status, age, age squared, indicator variable for race and gender. Main equation controls for year fixed effects. Specification (2) is the same as first with age indicator variables (3) Survival time regression adjustment estimation for survival analysis multivalued treatment with age indicator variables (no balance analysis available) (4) second specification for black subsample (5) second specification for female subsample

Next, we turn to our main and preferred specification where we include all occupational credentials altogether. We refer interested readers to Tables 11-14 in Appendix C where we present standardized difference and variance ratios of all independent variables. 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 9.

As you can see from Table 9, and similar to what we found in Table 8, when we include all occupational credentials we obtain similar results direction-wise but slightly bigger in magnitudes. Some important observations our in order. First, we consistently find that certificates issued by businesses have larger effects on unemployment duration than licensing—this effect is consistent for all specifications using propensity score matching. Second, some of the results we observed for specific groups are markedly different using this approach. Most notably, with propensity score matching, we now observe that business certification (much like what we found for in all of our previous estimations) effectively reduces unemployment duration. In short, we consistently find evidence that business certificates reduce unemployment duration for black workers, but the effect for women is more dependent upon our estimation strategy.

4.3 Discussion

Our paper is a first attempt at understanding how occupational licensing and certification affects unemployment duration. Our results suggest that credentials issues by businesses are almost always more effective at reducing unemployment duration than occupational licensing. Tying this empirical approach with our theoretical model suggests that certificates issued by business provide a stronger signal of ability or increase human capital more than occupational licenses. 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 estimation. It is important to note, however, that our results are robust direction-wise for licenses and certificates issued by businesses using a propensity score matching approach. Second, certificates 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 were not able to control for occupation in any of our specifications given the low sample of unemployed workers that report this data in the SIPP.

In future work, this question should be explored further with richer data sets that lack this limitation. 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. Unfortunately, our data set do not allow us to explore each of these separately. 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.

5 Conclusion

This paper introduces a novel extension of a job search and matching model to study the effects of certificates and licenses on individual unemployment duration. Our model's results are tested in an empirical setting. Heterogeneity in the signaling strength of licensing and certificates results in different effects on unemployment duration. We find consistent evidence that certificates issued by businesses are more effective at reducing unemployment duration than licensing. We also find that the effect of business certificates on unemployment duration is stronger for black workers relative to white workers. Thus, although licensing is the strictest form of occupational regulation, certificates issued by businesses appear to serve as better and more effective signals of worker ability. The gap in the effectiveness of business certificates relative to licensing in reducing unemployment duration is between 15 and 24 days pending on our empirical specification.

As policy makers across the world reevaluate the costs and benefits of occupational licensing, our results indicate that certificates issued by businesses may provide larger human capital improvements to people who search for jobs as well as provide more information to prospective employers than government issued licenses. Workers also have a choice when considering whether to acquire a certificate, but with licensing the decision is mandated by law. Certificates issued by businesses may provide a more efficient mechanism for workers to improve human capital as well as signal ability without the associated costs of mandated licensing.

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6 Appendix A

6.1 Preferences

In each period, consumption goods are bought with labor income. Let us fix the number of hours worked and assume them to be homogeneous across all occupations. Workers' preferences are represented by a utility function over intertemporal unordered tuples of leisure and consumption. As in Mortensen (1977), the typical worker's choice problem is a Markov decision process where each state space contains the options of not participating, searching while unemployed, and working. The key choice variables are reservation wage and search intensity.

Let y_j be the goods per period bought with labor income at date j and let l_j denote time spent on leisure as the share of the interval $(j, j + h)$. As in Mortensen (1977), utility is intertemporally separable and has the following functional form.

$$U_j = \frac{1}{1+rh}\left[hu\left(y_j, l_j\right) + U_{j+h}\right] \quad (14)$$

where $u(\cdot)$ is the utility derived from (y_j, l_j); r is the sum of subjective discount rate and the probability of retiring per period when $u(0,l) = 0$ and h is a time period.

As in Mortenensen (1977), depending on the state, (y,l) has the following forms.

$$(y, l) = \begin{cases} (0,1) & \textit{not participating in the labor market} \\ (b, 1-s) & \textit{unemployed worker who searches} \\ (w, l_0 - s) & \textit{employed worker who searches} \end{cases} \quad (15)$$

where b is the benefit[20] and s is the search intensity in the current period. Thus, $b = 0$ for unemployed individuals who are not qualified for unemployment benefits. For employed workers who search, w is the wage and $l_0 < 1$ is the fraction of time after work.

In general, offers arrive for unemployed workers with the following probability.

$$Pr(offer\ arrives) = \underbrace{\alpha sh}_{fraction\ of\ h\ devoted\ to\ search} \tag{16}$$

Where h is a time interval, s is a search intensity and α can be thought of the extent to which an individual who searches for a job has access to different occupations. In other words, α reflects how many job opportunities an occupational credential opens for an individual. The higher the search intensity s, the strength of an occupational credential α, or both, the higher the probability of job offers arrival.

We allow α to vary depending on whether an individual has access to occupations based on having a license (α_1) or a certificate (α_2). Search effort s is allowed to vary between licensed (s_1) and certified individuals (s_2). Since the time it takes for an occupational credential to expire is longer than most unemployment durations, we believe we can safely assume that occupational credential do not expire earlier than when an individual finds a job.

The probability of a worker being laid off is constant and not affected by worker's decisions. Thus, the probability of a worker being laid off in an interval of length h is $h\delta$.

Search is random such that wage offers arrive as a random draw from the known distribution $F(w)$. We model two regulatory regimes that result in two types of occupational credentials i.e. licensing and certification. Thus, there are two wage-offer distributions $F_1(w)$ for licenses and $F_2(w)$ for certificates. Let us introduce the following assumption.

[20] If T is the length of the maximum unemployment benefit period and t is the time for which a worker has been laid off, then unemployed worker qualified for benefits has a remaining benefit period $T - t$.

Assumption 1 *Since licensing increases wages in licensed occupations and certification is a less strict regime, 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*[21] $F_2(w)$.

If $\overline{w}_1$ and $\overline{w}_2$ are maximum attainable wages under licensing and certification, then $\overline{w}_1 > \overline{w}_2$ and $F_1(\overline{w}_1) = 1$ as well as $F_2(\overline{w}_2) = 1$. Although, to our knowledge, there was no study that directly tested assumption 1, papers by Kleiner and Krueger (2013) for the US as well as Koumenta et al (2022) for Europe indicate that licensing wage premium is higher than certification wage premium.

6.2 The decision process

As in Mortensen (1977), an individual faces three options: no participation; unemployed and searching; and employed and searching. Hence, an individual makes the choice to 1) participate or not in the labor market and 2) accept or decline a job offer. Unemployment benefits enter the utility function and might affect reservation wages. Thus, we include unemployment benefits in the model. Next, we define preferences for a participant from a revealed preference argument. An individual participates in the job market if

$$U_0 > \underbrace{\frac{u(0,1)}{r}}_{present\ value\ of\ future\ utility\ flow\ in\ no\ participation} \tag{17}$$

An individual accepts a job if

$$U \geq U_0 \tag{18}$$

[21] Thus $F_1(w) \leq F_2(w) \Longrightarrow 1 - F_1(w) \geq 1 - F_2(w)$.

For a laid off worker i.e. a worker who is eligible for unemployment benefits, the condition to accept a job is

$$U \geq U_t \,\forall\, 0 \leq t \leq T \tag{19}$$

We denote $U = U(w,U_T)$ as the indirect expected utility of being employed at wage w where U_T is the indirect expected utility of being laid off at a future date.

Let $U_t = V\,(t,b,U_T)$ be the indirect utility of being unemployed with a future benefit period of length t to receive benefit b where U_T is the indirect utility of being laid off at the next job.

The indirect utility of being laid off is as follows

$$U_T = V\,(T,b,U_T) = \theta(T,b) \tag{20}$$

Search decisions are modelled as follows. If h is the length of the period and s_i is the fraction of period spent on search where i = 1 for licensed individuals and i = 2 for certified individuals. Utility during period h is as follows

$$hu(w,l_0 - s_i) \tag{21}$$

We not turn to the probabilities of changing states. Here we introduce a variable μ_i which denotes the strength of a signal from an occupational credential that might affect probability of finding a job where i denotes an occupational credential. The strength of the signals that licenses and certificates send to prospective employers can be different. The probability of being laid off is δh, the probability of finding a higher paying job is $\alpha_i\mu_i s_i hPr(x \geq w)$, and the probability of neither is $1{-}\delta h{-}\ \alpha_i\mu_i s_i hPr(x \geq w)$. Where δ is the layoff frequency, $\alpha_i\mu_i s_i$ is the frequency with which offers are generated given the search intensity s_i, and x is a randomly drawn offer from $F(x)$. Thus, the expected utility of being laid off is U_T, the expected utility of finding higher paying job is $E(U(x,U_T)|x \geq w)$, and the expected utility of having neither is $U(w,U_T)$.

Using principles of dynamic programming, an individual when employed has the following utility

$$U = U(w, U_T) =$$

$$= \frac{1}{1+rh} \underset{0 \le s_i \le l_0}{max} \big[hu(w, l_0 - s_i) + \delta h U_T + \alpha_i \mu_i s_i h Pr(x \ge w) E(U(x, U_T \mid x \ge w)\big) + (1 - \delta h - \alpha_i \mu_i s_i h Pr(x \ge w) U(w, U_T))]$$

Since

$$\Pr(x \ge w) = \int_w^{\overline{w}} dF(x) = 1 - F(w)$$

and

$$\Pr(x \ge w)\, E(U(x, U_T)|x \ge w) = \int_w^{\overline{w}} U(x, U_T) dF(x)$$

Thus

$$U = U(w, U_T) =$$

$$= \frac{1}{1+rh} \underset{0 \le s_i \le l_0}{max} [hu(w, l_0 - s_i) + \underbrace{\delta h[U_T - U(w, U_T)]]}_{expected\ loss\ from\ a\ layoff} + \underbrace{\alpha_i \mu_i s_i \int_w^{\overline{w}} [U(x, U_T) - U(w, U_T)] dF(x)}_{expected\ gain\ from\ a\ higher\ paying\ job} \qquad (22)$$

Consider $V(t, b, U_T)$ the indirect utility function for an unemployed worker. During h, the worker who is qualified for benefits receives utility flow $hu(b, 1-s_{it})$ where s_{it} is the search intensity as a share of time while remaining period of benefits is t. Here an offer x arrives with a probability of $\alpha_i\, \mu_i s_{it}\, h$. If the current reservation wage w_t is lower than the offer wage, then the offer is accepted. An unemployed worker chooses s_{it} and w_t to maximize expected future discounted utility flow given t.

The utility if a worker is employed.

$$U = U(x, U_T)$$

Otherwise, the indirect utility of being unemployed with the remaining benefit period $t - h$

$$U_{t-h} = V(t - h, b, U_T)$$

Then the indirect utility of being unemployed is the weighted average of U and U_{t-h} where weights are probabilities of realization of those states. Thus $\forall\ 0 < t \leq T$

$$U_t = V(t, b, U_T) =$$

$$= \frac{1}{1+rh} \max_{\substack{0 \leq s_{it} \leq 1 \\ w_t \geq 0}} [hu(b, 1 - s_{it}) + (1 - \alpha_i) s_{it} h Pr(x \geq w_t) V(t - h, b, U_T) + \alpha_i \mu_i s_{it} h Pr(x \geq w_t) E(U(x, U_T) | x \geq w_t)]$$

Equivalently, $\forall\ 0 < t \leq T$

$$V(t, b, U_T) = \frac{1}{1+rh} \max_{\substack{0 \leq s_{it} \leq 1 \\ w_t \geq 0}} [hu(b, 1 - s_t) + V(t - h, b, U_T) + \underbrace{\alpha_i \mu_i s_{it} h \int_{w_t}^{\bar{w}} [U(x, U_T) - V(t - h, b, U_T)] dF(x)]}_{total\ expected\ future\ indirect\ utility\ gain\ if\ job\ is\ found}$$

Both a person with expired benefits and a new entrant receive $b = 0$ and thus

$$U_0 = V(t, 0, U_T) = V(t - h, 0, U_T) = V(0, 0, U_T) \tag{23}$$

6.3 Search behavior and demand for leisure

The escape rate (q) is the expected frequency with which workers find acceptable offers. The escape rate is a product of the probability that an offer arrives during interval h and the probability that the offer is acceptable. The probability that a worker makes a transition from unemployment to employment in time interval h is hq. In our model, escape rates are also influenced by heterogeneity in the strength of our two types of occupational regulation, licenses, and certificates. Licensed individuals have access to a set of occupations that is captured by α_1 while certified individuals have access to another set of occupations which is captured by α_2. The strength of a signal is denoted as μ. The strength of the signals that licenses and certificates send to prospective employers can be different. The combination of the access to different occupations and a job market signal is $\alpha_1 \mu_1$ for licensed individuals and $\alpha_2 \mu_2$ for certified individuals. Thus, the main conclusion of the proposed model that follows below is that unemployment duration is expected to be shorter for occupational regulation that has larger human capital or signaling effects. The type of occupational regulation, licensing, or certification, that has a stronger effect remains a testable empirical question. Thus, escape rates are as follows.

$$q_1 = \alpha_1 s_1[1 - F_1(w)]\mu_1 \textit{ if licensed} \tag{24}$$

$$q_2 = \alpha_2 s_2[1 - F_2(w)]\mu_2 \textit{ if certified} \tag{25}$$

Following Assumption 1, escape rates will be greater for credentials having stronger effects adjusting for relative reservation wages and search efforts:

$$q_1 > q_2 \quad if \quad \alpha_1\, \mu_1 > \alpha_2\, \mu_2 \frac{[1-F_2(w)]s_2}{[1-F_1(w)]s_1} \tag{26}$$

Otherwise,

$$q_2 > q_1 \quad if \quad \alpha_2\, \mu_2 > \alpha_1\, \mu_1 \frac{[1-F_1(w)]s_1}{[1-F_2(w)]s_2} \tag{27}$$

For our first case, let us examine employed search. As in Mortensen (1977), assume that real income and leisure are complements i.e. $\frac{\partial^2 u}{\partial y \partial l} > 0$. If $0 < s_i < 1$ and $w > 0$, then maximization problem for $V\,(t,b,U_T)$ implies (w^*,s^*) satisfy

$$\underbrace{U(w^*, U_T)}_{employment\ at\ reservation\ wage} \quad = \quad \underbrace{V(t, b, U_T)}_{remain\ unemployed} \quad (28)$$

(28)

and

$$\underbrace{\frac{\partial u(b,1-s_i{}^*)}{\partial l}}_{marginal\ utility\ of\ time\ in\ leisure} \quad = \quad \underbrace{\alpha_i \mu_i \int_w^{\overline{w}} [U(x, U_T) - V(t, b, U_T)] dF(x)}_{marginal\ indirect\ utility\ gain\ due\ to\ search} \quad (29)$$

For our second case, we consider unemployed search with unemployment benefits.

$$U(w^*,U_T) = V\,(T,b,U_T) = U_T \tag{30}$$

and

$$\underbrace{\frac{\partial u(b,1-s_i{}^*)}{\partial l}}_{marginal\ utility\ of\ time\ in\ leisure} \quad = \quad \underbrace{\alpha_i \mu_i \int_w^{\overline{w}} [U(x, U_T) - U_T] dF(x)}_{marginal\ indirect\ utility\ gain\ due\ to\ search}$$

Finally, consider the case of unemployed search without unemployment benefits i.e., b = 0.

$$\underbrace{U(w^*, U_T)}_{utility\ of\ being\ employed} = \underbrace{V(0,0,U_T)}_{utility\ of\ being\ unemployed} \tag{32}$$

and

$$\underbrace{\frac{\partial u(0,1-s_i{}^*)}{\partial l}}_{marginal\ utility\ of\ time\ in\ leisure} = \underbrace{\alpha_i \mu_i \int_w^{\overline{w}} [U(x, U_T) - V(0,0,U_T)] dF(x)}_{marginal\ indirect\ utility\ gain\ due\ to\ search} \tag{33}$$

6.4 Expected unemployment duration

Receiving 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 fully qualified. We will consider the case where a worker is not qualified for unemployment benefits. 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

$$D^0 = \int_0^\infty v q^0 exp^{-q^0 v} dv = 1/_{q^0} \quad (5)$$

Here, the augmented model allows us to compare the heterogeneous effects of licensing and certification on duration through escape rate q^0. Thus, the unemployment duration of workers who have a license is shorter than duration of workers who have a certificate if

$$D_1^0 < D_2^0 \ if \ \ 1/_{q_1^0} < 1/_{q_2^0} \rightarrow q_1^0 > q_2^0 \quad (6)$$

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).

7 Appendix B

Kaplan-Meier estimates for individual occupational credentials as well as for different occupational credentials are presented in Figures 2-6.

The lines in Figure 6 represent survival estimates. The lower the line the lower the probability of surviving in the next period, i.e. staying unemployed in the next period, the lower the better for escaping the state of unemployment.

As shown in Figure 6, licensing increases the probability of escaping from unemployment (long dashed line compared to the grey solid line). Licensing generally performs better than certification with the exception of business-issued certificates. Consistent with our previous analysis, workers with business certificates have a higher probability of escaping employment than workers with licenses.

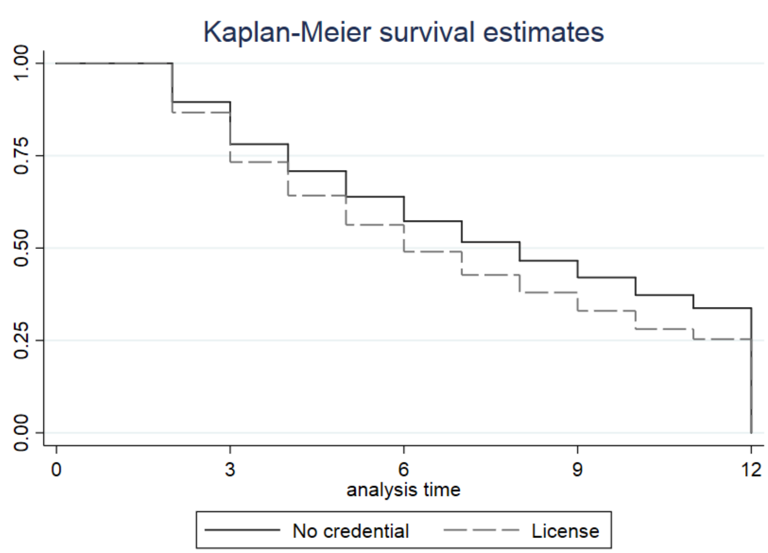

Figure 2: Kaplan-Meier estimates for survival function by license indicator variable

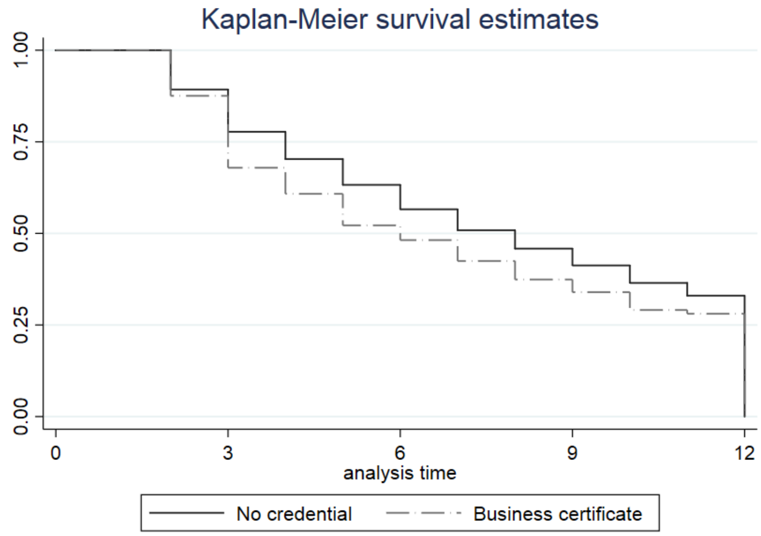

Figure 3: Kaplan-Meier estimates for survival function by business certificate indicator variable

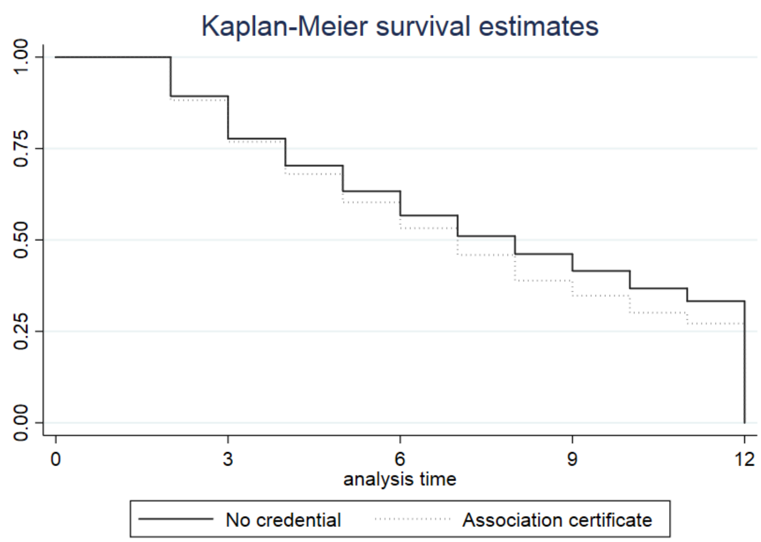

Figure 4: Kaplan-Meier estimates for survival function by association certificate indicator variable

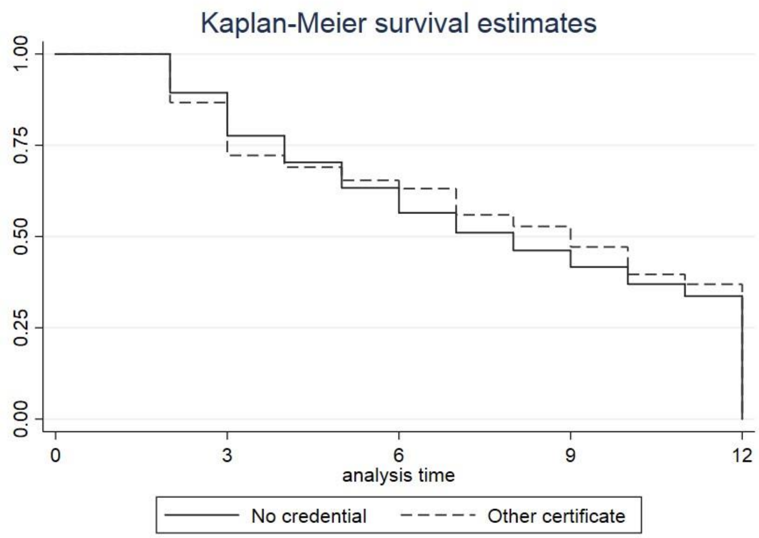

Figure 5: Kaplan-Meier estimates for survival function by other certificate indicator variable

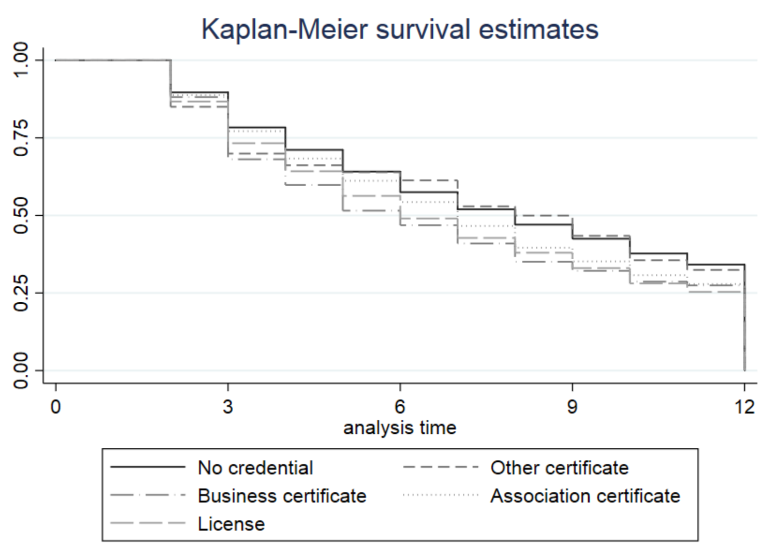

Figure 6: Kaplan-Meier estimates for survival function by occupational credential.

8 Appendix C

Table 10. Summary statistics for independent variables used in the analysis.

	Mean	St.Dev	Min	Max
Indicator if an individual is not a citizen of the United States	.08	.27	0	1
Indicator for classes to improve basic reading or math skills	.01	.11	0	1
Indicator for job readiness training to learn about resume writing, job interviewing, or building self-esteem	.03	.17	0	1
Indicator for job search program or job clubs, or use any job resource centers to find out about jobs, to schedule interviews, or to fill out applications	.06	.24	0	1
Indicator for training to learn specific job skills, such as computers, car repair, nursing, day care work, or some other job skills	.04	.18	0	1
Indicator for training or using job resources because it was required	.00	.02	0	1
Indicator for training or using job resources because it was a choice	.00	.06	0	1
Indicator for training or using job resources because it was both required and a choice	.00	.04	0	1
Indicator for whether the individual reported spending some time on layoff for a no-job spell associated with the given month.	.09	.29	0	1

Average weekly wage from the first job	12.84	95.55	0	4026
Amount of regular, government-provided Unemployment Compensation payments received in each month of reference period	572.06	711.02	0	4380
Age as of last birthday	36.00	13.42	18	65
Age as of last birthday squared	1469.00	1054.85	324	4225
Indicator if age is below 36 years	0.55	.50	0	1
Indicator if age is from 36 to 50 years	.26	.44	0	1
Indicator if age is above 51 years	.20	.40	0	1
Indicator if an individual considers herself/himself to be White alone	.68	.47	0	1
Indicator if an individual considers herself/himself to be Black alone	.22	.41	0	1
Indicator if an individual considers herself/himself to be Asian alone	.04	.21	0	1
Indicator if an individual considers herself/himself to be Other than White, Black, or Asian alone	.06	.23	0	1
Indicator if gender is female	.48	.50	0	1
Indicator if an individual's highest level of school is at most high school	.52	.50	0	1
Indicator if an individual has some college credit but no degree	.23	.42	0	1

Indicator if an individual has a college degree and above	.25	.44	0	1

Note: 2013-2019 from the Survey of Income and Program Participation (SIPP) data

Table 11. Balance analysis for specification (1) Table in 8

	(1) St. Dif. raw	(1) St. Dif. weighted	(1) Var ratio raw	(1) Var ratio weighted
	License			
Indicator if an individual is not a citizen of the United States	-.144	.042	.594	1.133
Age as of last birthday	.345	.024	.972	.970
Age as of last birthday squared	.318	.017	1.086	1.014
Indicator if an individual considers herself/himself to be White alone	.092	-.004	.925	1.003
Indicator if an individual considers herself/himself to be Black alone	-.075	-.000	.896	1.000
Indicator if an individual considers herself/himself to be Asian alone	-.024	.016	.900	1.071
Indicator if gender is female	.150	.027	.992	1.001
	Certificate business			
Indicator if an individual is not a citizen of the United States	-.011	.100	.969	1.332
Age as of last birthday	.313	.065	1.198	.980
Age as of last birthday squared	.322	.056	1.333	1.021
Indicator if an individual considers herself/himself to be White alone	-.132	-.156	1.084	1.096
Indicator if an individual considers herself/himself to be Black alone	.106	.109	1.138	1.142
Indicator if an individual considers herself/himself to be Asian alone	.042	.121	1.187	1.577
Indicator if gender is female	-.480	-.115	.756	.980

	Certificate association			
Indicator if an individual is not a citizen of the United States	-.171	.019	.525	1.059
Age as of last birthday	.315	.017	.905	.982
Age as of last birthday squared	.277	.012	.997	1.022
Indicator if an individual considers herself/himself to be White alone	-.037	.015	1.027	.988
Indicator if an individual considers herself/himself to be Black alone	.019	.010	1.025	1.014
Indicator if an individual considers herself/himself to be Asian alone	.007	-.029	1.030	.877
Indicator if gender is female	.103	.005	.999	1.000
	Certificate other			
Indicator if an individual is not a citizen of the United States	.053	-.008	1.17	.97
Age as of last birthday	.147	-.007	1.115	.983
Age as of last birthday squared	. 151	-.009	1.217	1.022
Indicator if an individual considers herself/himself to be White alone	-.046	.005	1.033	.996
Indicator if an individual considers herself/himself to be Black alone	.055	-.004	1.073	.994
Indicator if an individual considers herself/himself to be Asian alone	.027	.012	1.121	1.053
Indicator if gender is female	-.078	-.021	.988	.998
N	125,747	125,747	125,747	125,747

Table 12. Balance analysis for specification (2) Table 8

	(2) St. Dif. w/o	(2) St. Dif. with	(2) Var ratio w/o	(2) Var ratio with
	License			
Indicator if an individual is not a citizen of the United States	-.144	.036	.594	1.117

Indicator if age is below 36 years	-.282	-.001	.997	1.000
Indicator if age is above 51 years	.223	.002	1.348	1.003
Indicator if an individual considers herself/himself to be White alone	.092	-.017	.925	1.013
Indicator if an individual considers herself/himself to be Black alone	-.075	.014	.896	1.019
Indicator if an individual considers herself/himself to be Asian alone	-.024	.020	.900	1.089
Indicator if gender is female	.150	.015	.992	1.001
Certificate business				
Indicator if an individual is not a citizen of the United States	-.011	.120	.969	1.400
Indicator if age is below 36 years	-.239	-.028	1.009	1.004
Indicator if age is above 51 years	.299	.046	1.448	1.072
Indicator if an individual considers herself/himself to be White alone	-.132	-.166	1.084	1.100
Indicator if an individual considers herself/himself to be Black alone	.106	.105	1.138	1.136
Indicator if an individual considers herself/himself to be Asian alone	.042	.133	1.186	1.638
Indicator if gender is female	-.480	-.102	.756	.983
Certificate association				
Indicator if an individual is not a citizen of the United States	-.171	.020	.525	1.065
Indicator if age is below 36 years	-.251	.014	1.006	.997
Indicator if age is above 51 years	.172	-.005	1.274	.993
Indicator if an individual considers herself/himself to be White alone	-.037	.003	1.027	.997
Indicator if an individual considers herself/himself to be Black alone	.019	.012	1.025	1.016
Indicator if an individual considers herself/himself to be Asian alone	.007	-.014	1.030	.941
Indicator if gender is female	.103	-.001	.999	1.000
Certificate other				
Indicator if an individual is not a citizen of the United States	.053	-.006	1.166	.981

Indicator if age is below 36 years	-.144	-.004	1.019	1.001
Indicator if age is above 51 years	.076	.005	1.127	1.007
Indicator if an individual considers herself/himself to be White alone	-.046	.002	1.033	.998
Indicator if an individual considers herself/himself to be Black alone	.055	-.006	1.073	.991
Indicator if an individual considers herself/himself to be Asian alone	.027	.011	1.121	1.049
Indicator if gender is female	-.078	-.020	.988	.998
N	125,747	125,747	125,747	125,747

Table 13. Balance analysis for specification (4) Table 8

	(2) St. Dif. w/o	(2) St. Dif. with	(2) Var ratio w/o	(2) Var ratio with
	License			
immigrant	.147	.017	1.85	1.09
age35	-.306	-.025	1.03	1.01
age36_50	.171	.029	1.19	1.03
gender	.195	.020	.959	1.00
	Certificate business			
immigrant	-.089	-.150	.592	.384
age35	-.177	-.057	1.04	1.01
age36_50	-.351	.052	.528	1.06
gender	-.135	.063	.989	.992
	Certificate association			
immigrant	.034	.038	1.18	1.19
age35	-.236	.027	1.03	.991
age36_50	-.013	-.047	.985	.942

gender	.229	.013	.944	.998
	Certificate other			
immigrant	-.060	.024	.721	1.12
age35	-.161	.022	1.04	.993
age36_50	.168	-.043	1.19	.947
gender	-.248	.062	.949	.992
N	27,445	27,445	27,445	27,445

Table 14. Balance analysis for specification (5) Table 8

	(2) St. Dif. w/o	(2) St. Dif. with	(2) Var ratio w/o	(2) Var ratio with
	License			
immigrant	-.180	.023	.533	1.07
age35	-.185	.016	.992	.999
age36_50	.038	-.017	1.04	.983
Race1	.100	-.015	.925	1.01
race2	-.064	.020	.918	1.03
race3	-.024	-.001	.898	.997
	Certificate business			
immigrant	.292	.069	1.87	1.00
age35	-.341	-.024	.939	1.00
age36_50	-.070	-.111	.932	.887
Race1	-.758	-.000	.942	1.00
race2	.495	.034	1.39	1.05
race3	.390	.017	3.01	1.07
	Certificate association			

immigrant	-.190	.018	.509	1.05
age35	-.219	.017	.984	.998
age36_50	.106	-.016	1.09	.985
Race1	-.102	-.005	1.06	1.00
race2	.078	-.000	1.09	1.00
race3	.019	.009	1.08	1.04
	Certificate other			
immigrant	-.180	.023	.992	1.07
age35	-.185	.016	.992	.999
age36_50	.039	-.017	1.04	.983
Race1	.101	-.014	.925	1.01
race2	-.064	.020	.918	1.03
race3	-.025	-.001	.898	.997
N	60,820	60,820	60,820	60,820