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The Influence of Occupational Licensing on Workforce Transitions to Retirement

Yun taek Oh[1] | Morris M. Kleiner[2,3,4]

[1]Department of Economics, University of Nevada, Reno, Reno, Nevada, USA | [2]Humphrey School of Public Affairs, University of Minnesota, Minneapolis, Minnesota, USA | [3]National Bureau of Economic Research, Cambridge, Massachusetts, USA | [4]University of Minnesota, Stanford University, Federal Reserve Bank of Minneapolis, and Hoover Institution, Minneapolis, Minnesota, USA

Correspondence: Yun taek Oh (yuntaeko@unr.edu)

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ABSTRACT

Ways of leaving the labor force have been an understudied aspect of labor market outcomes. Labor market institutions such as occupational licensing may influence how individuals transition to retirement. When and how workers transition from career jobs to full retirement may contribute to pre- and post-retirement well-being. Previous investigations of retirement pathways focused on the patterns and outcomes of retirement transitions, yet the influence of occupational licensing on retirement transition has not been analyzed. In this study, we use the Current Population Survey to investigate how occupational licensing influences American later-career workers' choice of retirement pathways. Our results show that older licensed workers are less likely to choose to make career transitions but more likely to reduce work hours in transitioning out of the labor force. These results are consistent with the findings that licensed workers receive more benefits in the form of preferable retirement options, suggesting that these workers tend to have higher wages, benefits, and flexibility even toward the end of their careers.

JEL Classification: J0, J26, J3, J30, J32, J33, J40, J44

1 | Introduction

Increasing longevity has increased the duration of labor force participation and diversified the ways older workers exit the workforce (Cahill and Quinn 2020). A recent report from the National Academies of Sciences, Engineering, and Medicine (2022) shows that the proportion of workers aged 60 and above in the United States doubled from 7.4% to 14.8% for men and from 6.3% to 14.0% for women between 2000 and 2020. This result suggests that a significant proportion of the current workforce is at the end of their work lives and will take different pathways before completely exiting the workforce. To understand the patterns and outcomes of retirement transitions, previous studies have investigated retirement pathways (Berkman and Truesdale 2023; Cahill, Giandrea, and Quinn 2006, 2012, 2018; Gustman and Steinmeier 2000; Ruhm 1990, 1991; Quinn 1999). While these studies evaluated the influence of numerous socioeconomic factors on retirement pathways and retirement outcomes, the role of labor market institutions in the process of retirement transition has not been evaluated.

Occupational licensing has been one of the fastest-growing labor market institutions in the United States. About one in four workers have attained a license from the government, with even more covered by statutes (Gittleman and Kleiner 2016; Cunningham 2019). Previous studies provided theoretical and empirical evidence that licensed workers tend to have higher productivity, which allows these workers to receive higher wages and more fringe benefits (Kleiner 2000; Gittleman, Klee, and Kleiner 2018; Smith and Ehrenberg 1983). Using the sample of older workers in the Current Population Survey (CPS), we evaluate how occupational licensing influences the choice of retirement pathways of older workers in the United States, which eventually leads these workers to remain in their career jobs by choosing preferable retirement options as a fringe benefit.

To preview our findings, initially we show that, as is consistent with other studies, having an occupational license reduces cross-occupational mobility for older workers (Kleiner and Xu 2024). Second, having an occupational license is related to fewer losses that are associated with full-time careers, and in contrast to unlicensed employees, licensed workers can choose to reduce work hours toward the end of their careers (Han and Kleiner 2021). We also provide robust results by conducting the same estimations with different populations. For instance, we show that older workers' retirement transitions are different from younger workers' career transitions because younger workers' occupational licenses reduce cross-occupational mobility but increase cross-employer mobility: a way to develop one's career. We also show that longer job tenure is associated with career benefits that let the occupational license playing a crucial role in determining older workers' preference for retirement pathways. Overall, having an occupational license gives workers greater flexibility and voice within the organization, even at the end of their careers.

Our paper provides two innovative contributions to the literature. First, our study examines the benefits of occupational licensing that covers 78% of licensed occupations (129 of 166 occupations). Previous studies largely cover the extensive margin of the benefits of occupational licensing (e.g., Kleiner 2006; Kleiner and Krueger 2013; Gittleman, Klee, and Kleiner 2018; Kleiner and Soltas 2023). Their findings show the general benefits that licensed workers have from the impacts of restricted labor supply and higher productivity. This study focuses on a specific benefit of occupational licensing that is important during the latter phase of careers and post-retirement well-being. Second, this is the first study that evaluates the impact of occupational licensing on older workers' retirement transition.

The remainder of this paper is organized as follows. In Section 2, we present the literature review on retirement transition and pathways and the theories explaining how occupational licensing may influence workers' choices. In Section 3, we provide a detailed explanation of the datasets, sample selection, and definitions of variables used in this study. In Section 4, we explain the methods for the estimation and robustness checks. In Section 5, we outline the results from the baseline analyses and robustness checks and provide implications for the findings. In the final section, we summarize the findings and implications and provide a discussion of limitations and suggestions for future studies.

2 | A Review of the Literature and Theoretical Framework

Retirement transition has been diversified over time; instead of directly exiting the labor force at once from career jobs (often called "traditional retirement"), transitioning from career jobs to full retirement by choosing various work adjustments has been common for at least a half-century. Ruhm (1990) analyzes the Retirement History Longitudinal Survey (RHLS) and shows that between 1969 and 1979, 60% of household heads took some form of work adjustments that smoothed the processes of retirement transition. These work adjustments include switching from career occupations to new occupations, leaving career job employers to new employers, and slowly reducing work hours over time. These adjustments are called "bridge employment" because they bridge between career jobs and complete withdrawal from the labor force by adjusting work settings such as occupations, employers, or work hours (Ruhm 1991; Alcover et al. 2014).

Across disciplines, the consensus on the definition of bridge employment is that it is a type of paid work placed after the main career job and before the complete withdrawal from the labor force (Topa et al. 2014; Oh 2024). These transitions can occur in the same or different occupations and employers, in full- or part-time work, and on a regular or temporary basis. In addition, there are various reasons why older workers choose to take on bridge employment. For instance, some workers want to have more control over their lives—for example, by having a more flexible schedule or trying challenging new jobs before leaving the workforce (Pengcharoen and Shultz 2010; Ulrich and Brott 2005). Some workers want to alleviate the physical demands of working (Cahill, Giandrea, and Quinn 2012; Giesecke and Okoampah 2014). Other workers want to stay in the labor force longer and accumulate more retirement savings and pensions (Clark 1988; Gustman and Steinmeier 1991). The above list of accommodations for older workers allows us to posit bridge employment as a fringe benefit because the way it offers a time to "phase out" from the labor force which contributes to well-being during and after retirement—for example, through better health outcomes and more retirement savings (Alcover et al. 2014; Kim and Feldman 2000; Zhan et al. 2009). Taking bridge employment can be done only after employers' offers, except in the case of transitioning to self-employment.

From an economic perspective, categorizing retirement pathways is relevant in terms of evaluating the economic costs and benefits of different types of bridge employment to reduce labor force participation and hours of work. In this study, we develop a typology by creating three categories of bridge employment. First, switching occupations is a move from the occupation of one's career job to another occupation that is not related to promotion. Second, leaving career job employers is a move from the employer of one's career job to another employer. Last, reducing work hours is a change in one's work hours from full- to part-time. These categories of bridge employment can overlap. For instance, a full-time registered nurse at a university hospital quitting her job and becoming a part-time nurse at a local clinic involves two categories of bridge employment—leaving career job employers and reducing work hours—at once.

Given the three categories of bridge employment and how they can overlap, it is possible to distinguish between two mutually exclusive groups: One that loses career benefits, such as higher wages and benefits, from taking bridge employment, and one that does not. For instance, switching occupations involves a loss in the application of occupation-specific human capital and skills and may lead to wage loss (Kleiner and Xu 2024; Robinson 2018; Shaw 1987). Similarly, leaving career job employers involves a loss of firm-specific human capital and tenure effect, which also may lead to this loss (Buchinsky et al. 2010; Burdett and Coles 2003; Dustmann and Meghir 2005; Gagliardi, Grinza, and Rycx 2023; Topel 1991). Reducing work hours in career jobs does not always involve the loss of career benefits; there is no loss in the occupation- and firm-specific human capital or tenure effect since the employee is working for the same employer and doing the same occupational tasks but with reduced hours. Of course, it can involve a loss of career benefits if it is done via switching occupations or employers. Thus, bridge employment by reducing work hours within career jobs, often called "phased retirement," is different from the other categories of bridge employment because it does not involve the loss of career benefits that leads to wage loss.

Because it does not involve a loss of career benefits, phased retirement is the preferred form of bridge employment for older workers choosing from multiple retirement pathways. However, phased retirement is the least common pathway among the bridge employment categories (Cahill and Quinn 2020). Hutchens (2010) provides the reason why it is not common: While taking on phased retirement requires an employer's consent, employers are willing to offer phased retirement to workers who have certain characteristics related to higher productivity, comprehensiveness, work independence, and higher performance.

This result is also consistent with economic theory. Lazear and Shaw (2007) show that employers are willing to provide more wage and fringe benefits to attract more productive workers; a hedonic model of compensation presents the tradeoff between wages and fringe benefits, finding that the worker with higher productivity tends to have higher utility by receiving higher wages and more fringe benefits (Eriksson and Kristensen 2014; Smith and Ehrenberg 1983). Since licensed workers tend to have higher productivity and wages (Kleiner 2000), they are more likely than unlicensed workers to receive more fringe benefits. Furthermore, occupational licensing limits labor supply and employment, and licensed workers are thereby put in favorable labor market positions in regulated occupations (Blair and Chung 2024; Kleiner and Soltas 2023). Previous studies provide evidence that licensed workers tend to receive more fringe benefits such as employer-sponsored health insurance and job security (Gittleman, Klee, and Kleiner 2018; Kleiner and Krueger 2013; Nunn 2018).

We suggest two hypotheses based on the above theoretical implications. First, licensed workers are less likely to choose retirement pathways that involve the loss of career benefits, such as switching occupations or leaving career job employers. Getting a license may show that regulated workers have an added commitment to the occupation and may want to leave work at a slower pace. Second, licensed workers are more likely to choose retirement pathways that do not involve significant loss of career benefits, such as phased retirement. The economic leverage of having an occupational license may allow the workers to have this benefit in addition to wages and other fringe benefits (Kleiner and Krueger 2013).

3 | Data

3.1 | Current Population Survey (CPS)

To investigate the effect of occupational licensing, we mainly use the IPUMS Current Population Survey (CPS) Outgoing Rotation Group (ORG) from October 2017 to April 2023 to evaluate how occupational licensing influences the choice of retirement pathways (Flood et al. 2023). The sample of respondents are workers between the ages of 51 and 63[1] who have full-time career jobs in the first wave. Approximately one-quarter of the CPS respondents are chosen for the ORG data collection and receive additional labor questions in the fourth and eighth waves of the survey, including questions about labor income that are used for the estimation procedure. The labor questions are asked in the fourth and eighth waves, and some workers take on bridge employment in the second or third waves, which precludes the observation of the labor income from full-time career (FC) jobs. Thus, we drop the data of respondents who take on bridge employment before their first labor income data are collected.

To define FC jobs, we follow the definition suggested in the previous studies: working full-time (1600+ hours annually) for 10+ years in the same job (Cahill, Giandrea, and Quinn 2006; Quinn 1999). Maintaining FC jobs before bridge employment is the necessary initial condition because the role of bridge employment is to smooth the transition from career jobs to complete withdrawal from the labor force. To obtain the number of years worked in the jobs, we use the variables provided in the CPS Job Tenure Supplement (JTS), also known as the Employee Tenure and Occupational Mobility Supplement, which since 2002 has been collected every other year in January.[2] The respondents who entered the survey between October of the odd year and January of the even year are asked to answer the job tenure questions if they participated in the survey in January of the even year. We assume that respondents are in their FC jobs in the first wave if they have 10+ years of job tenure in January of the even year and "usually and currently" work full-time in the first wave.

From 2015 onward, the CPS has included a set of variables on occupational licensing attainment, which is more specific than if an occupation is covered by a statute. For the respondents aged 16 and above and not in the CPS Annual Social and Economic Supplements (ASEC), respondents were asked whether they have an active professional certification or license. If they answered yes to this question, then they were asked two additional questions about their certification or license that were added to the CPS in 2016. To define the active occupational licensing status, we use the answers to these two additional questions. The first question asks whether respondents have a government-issued professional certification or license and, if so, whether the license was issued by federal, state, or local government. The second question asks whether a certification or license is required to perform a job in their occupations. Respondents are defined as licensed workers if they answered yes to both questions. We exclude the sample of respondents whose FC occupations are either fully licensed or unlicensed.[3]

We categorize retirement pathways into five mutually exclusive categories and use them as a quinary-dependent variable, considering the overlaps between two or more types of bridge employment and direct exit from the labor force. First, "switching occupations" is defined as a move to an occupation that is in a different Standard Occupational Classification (SOC) group from the FC occupation without moving to different employers or reducing work hours to part-time. To avoid changes in occupation due to promotion, we exclude the switches to the occupations in the SOC group "Management Occupations."

Second, "leaving career job employers" is defined as a move to an employer that is different from the FC employer without switching to different occupations or reducing work hours to part-time. Third, "reducing work hours only" is defined as a reduction in weekly hours from full-time to part-time: fewer than 35 h per week. Fourth, "two or more pathways at once" is defined as having bridge employment that involves one or more changes at once. Last, "directly exiting the labor force" is defined as exiting the labor force directly from career jobs. For detailed information about the CPS sample selection and variable definitions, see Appendix A. Table 1 provides the descriptive statistics of the licensed and unlicensed respondents in the CPS, before and after matching, that are used in this study. Further explanation about matching is provided in the next section.

3.2 | Multiple Bridge Employment in Retirement Pathway and Solution

One issue with defining the respondents' retirement pathways is that they can have more than one type of bridge employment throughout the survey periods. For instance, a respondent can choose to switch occupations in the fifth wave, and then leave their FC employer in the eighth wave. Whether to consider these two changes as one unique retirement pathway or two separate types of bridge employment is a complex issue. Although treating multiple bridge employment as one unique pathway can be done using sequence analysis, it is not plausible in this study, since the number of possible combinations of retirement pathways exponentially increases as the time horizon of data increases. Since the main point of bridge employment is to leave one's career job, we document the first choice of the retirement pathway (i.e., the earliest bridge employment observed). In the example above, we define this respondent's bridge employment category as "switching occupations." If another respondent reduced work hours and left the FC employer at once in the same wave, then we define this respondent's bridge employment category as "two or more pathways at once."

4 | Empirical Framework

We use two different empirical strategies to conduct robust estimations of the influence of occupational licensing on the choice of retirement pathways. First, we mainly use competing risk analysis, obtaining sub-distributional hazard ratios that represent the likelihood of choosing a specific retirement pathway given the possibilities of choosing different pathways. We use this method for robustness checks using different samples of workers too. Second, as a robustness check, we use propensity score matching with coarsened exact matching to obtain the effect of occupational licensing on the choice of a specific retirement pathway over the other pathways by closely comparing the licensed and unlicensed workers with the same socioeconomic and demographic characteristics.

4.1 | Clustered Competing Risk Analysis With Propensity Score Matching

To obtain the influence of occupational licensing on the choice of retirement pathways, we use competing risk analysis (CRA). While standard time-to-event methods allow only a single type of event as a terminal outcome, a CRA allows multiple terminal outcomes (i.e., two or more types of

TABLE 1 | Descriptive statistics—Current Population Survey (CPS).

	Unlicensed workers				Licensed workers			
	Competing risk analysis		Matching estimations		Competing risk analysis		Matching estimations	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Observation	1422		1313		622		674	
Switching occupations	0.230	0.421	0.228	0.420	0.114	0.318	0.111	0.315
Leaving career job employers	0.056	0.231	0.058	0.234	0.095	0.293	0.101	0.301
Reducing work hours	0.013	0.115	0.017	0.128	0.043	0.204	0.037	0.189
Two or more pathways at once	0.026	0.159	0.027	0.163	0.026	0.158	0.024	0.152
Weekly earnings (US$)	1412	743	1510	733	1488	701	1555	711
Sex (1 = Female)	0.428	0.495	0.409	0.492	0.519	0.500	0.509	0.500
Spouse present	0.741	0.439	0.755	0.430	0.749	0.434	0.752	0.432
Race (1 = Non-White)	0.134	0.340	0.125	0.331	0.138	0.345	0.136	0.344
Education (1 = HS Grad or higher)	0.388	0.488	0.427	0.495	0.614	0.487	0.626	0.484
Age	56.8	3.6	56.8	3.6	56.6	3.7	56.6	3.7

Note: The samples are obtained from the IPUMS-CPS, 2017–2023 Outgoing Rotation Group and Job Tenure Supplement. The sample used in competing risk analysis is obtained using propensity score matching, and the variables used in the matching process include: sex, spouse presence, race and ethnicity, education, weekly earnings, and career occupations. Similarly, the sample used in matching estimations is obtained using coarsened exact matching and propensity score matching. The same set of variables listed above are used in the matching processes.

events) to be estimated using a set of covariates on the marginal probability function (Fine and Gray 1999). Competing risks is an event that precludes the occurrence of the event of interest (Austin, Lee, and Fine 2016). In a form of relative effect measures called "sub-distributional hazard ratio (SHR)," CRA estimates the marginal probability that the event of interest occurs using a cumulative incidence function. This is a function of cause-specific probability and overall survival probability, which allows us to calculate the SHR of the event of interest considering the SHRs of the other possible events (i.e., competing risks) (Fine and Gray 1999; Austin, Lee, and Fine 2016). Although it requires significantly more computing power, the first advantage of using CRA over multinomial estimation models is the higher degrees of freedom by analyzing one failure at a time while considering the SHRs of other failures. This is especially important in this study because the final sample size is relatively small compared with the number of covariates. Furthermore, since there are four retirement pathways as failures, in addition to not taking bridge employment, multinomial estimations are not feasible. In addition, the second advantage of using the CRA over multinomial estimations is that it allows taking the time-to-event into account, which is not doable in multinomial estimation models.

However, using an ordinary CRA is limited in obtaining the intended effects without a specific research design that accounts for the timing of policy impacts. To overcome this issue, we use the method introduced in Austin and Fine (2019): clustered competing risk analysis using propensity score matching. We first obtain the matched sample and propensity score using propensity score matching and then conduct CRA by clustering propensity scores. This method accounts for the within-pair clustering of outcomes that allows obtaining the average treatment on the treated (ATT).

To obtain a matched sample by licensing status, we first use socioeconomic and demographic variables including sex, spouse presence, race, education, weekly earnings, and FC occupations. During this step, we also obtain propensity scores for the respondents in the matched sample. Then, we add age, state of residency, and survey cohort,[4] in addition to the socioeconomic and demographic variables, into our time-to-event model. The estimation model is

$$\text{Prob}\left(Y_i = R\right) = \alpha + \delta L_i + \mathbf{X}_i \beta + \varepsilon_i \tag{1}$$

where R is the choice of a certain retirement pathway, L_i is the occupational licensing status, and $\mathbf{X}_i$ is the vector of socioeconomic and demographic variables. Furthermore, the subdistributional hazard ratios we obtain here are clustered by propensity scores obtained during the first step.

One issue with using CRA is that the non-linear cumulative incidence function is subject to the incidental parameter problem if the number of covariates in the estimation equation is large relative to the sample size. This issue leads the estimates to be inconsistent (Lancaster 2000; Neyman and Scott 1948). Since there are over 100 different career occupations in the CPS, adding a full set of career occupation indicators in the estimation equation will certainly make the estimates inconsistent. While the alternative empirical method to avoid this problem is to use multinomial regression with career occupation fixed effects, the permutation process required in this method requires a large sample size, which the available datasets lack.

To cope with this issue, we first substitute the career occupation indicators with the Standard Occupational Classification (SOC) group indicators, composed of 23 coarsely defined occupation groups, to reduce the number of covariates. In addition, we add five occupational composite measures obtained using the measures from the Occupational Information Network (O*NET) to separate the effect of licensing from the effects of occupational requirements from respondents' career jobs. O*NET provides abundant information on occupational characteristics and requirements that are evaluated by job analysts and is used in research to quantitatively represent occupational requirements (e.g., Peri and Sparber 2011; Casabianca, Turco, and Pigini 2020; Blasco, Rochut, and Rouland 2024). We follow the definitions of the following occupational composites from the Family Life Project (Crouter et al. 2006).

The first composite measure is the "self-direction" composite, which is the mean of the measures under the "occupational complexity" and "supervisory activities" categories. The ability to self-direct is an important aspect of working independently, which increases the likelihood of receiving "phased retirement" offers from employers (Hutchens 2010). Second, the "physically hazardous" composite is the mean of the measures under "situational stress." Third, the "physically active" composite is the mean of the measures under "physical activity and demand." Physical hazards and demand play significant roles in workers' decisions concerning early workforce exit and occupational and employer switching (Hayward et al. 1989; Sonnega et al. 2017). Fourth, the "interpersonal relations" composite is the mean of the measures under "interpersonal relations and care work." Some studies point out the importance of interpersonal relationships at work in the process of retirement transitions (e.g., Froidevaux, Hirschi, and Wang 2018; Wang and Huang 2024). Last, the "automation and repetition" composite is the mean of the measures under "routinization." Recent studies show that the de-routinization of work is positively associated with employment decline; these findings imply that the intensity of work routinization may influence the likelihood of switching occupations or employers (e.g., Consoli et al. 2023). Detailed information about the measures used for each composite is provided in Appendix B.

4.2 | Matching Estimation

In addition to CRA, we use propensity score matching (PSM) with coarsened exact matching (CEM) to cross-check the results for the robustness of the estimates. The advantages of using PSM are that it allows matching at the mean as well as reduces the imbalance of the distribution of observable characteristics across the treatment and control groups (licensed and unlicensed workers, respectively) in the process of estimating the treatment effect of occupational licensing. However, some studies suggest that PSM alone does not always reduce the imbalance but rather increases it (Iacus, King, and Porro 2012). Following the suggestion of the previous studies, we first conduct CEM to distinguish the samples with common support and then implement PSM using these samples. For the matching procedure, we use the following variables to balance between treatment and control groups: sex, spouse presence, race, education, weekly earnings, and FC occupations. Note that the FC occupation variable is not coarsened in the matching process in order to estimate with greater accuracy, even though there was a significant drop in the sample size. In addition to this list of variables, we introduce the variables including age, state of residency, and survey cohorts into the PSM estimation to obtain the effects of occupational licensing on the choice of retirement pathways. The estimation equation of the full model is

$$P(Y_i = R) = a + \gamma L_i + \mathbf{M}_i \eta + \overline{\mathbf{X}}_i b + \varepsilon_i \quad (2)$$

where R is the choice of a certain retirement pathway, L_i is the occupational licensing status, $\mathbf{M}_i$ is the vector of variables used for matching, and $\overline{\mathbf{X}}_i$ is the vector of variables not used in matching, which are age, state of residency, and survey cohorts for the estimations using the CPS.

While the advantage of using longitudinal data is its ability to account for the time-invariant unobserved heterogeneity, the use of PSM requires shrinking the longitudinal data into cross-sectional data, which loses this advantage and possibly introduces omitted variable bias into the estimation. Although adding control variables into the estimation models has been widely done to evaluate the influence of omitted variable bias, recent studies suggest that this method is not enough (Altonji, Elder, and Taber 2005; Oster 2019).

Following the suggestion of these studies, we use the evaluation method introduced in Oster. We first assume that the two correlations, the one between the treatment and unobservable and the one between the treatment and observables, have the same direction and magnitude. Then, we set the theoretical R-squared (R_{max}) as 1.3 times the R-squared from the full model and conduct a theoretical regression to obtain the coefficients that account for the theoretical influence of omitted variable bias; together with the estimated treatment effect, the estimated coefficients create lower and upper bounds to evaluate whether the unobservables overturn the result when higher explanatory power is assumed. Last, we obtain the value of delta when R_{max} is assumed, evaluating how big the unobservables would have to be to overturn the results. To provide more robust estimations, we repeat the second and last steps by imposing higher values of theoretical R-squared, further evaluating the size of the unobservable that can overturn the results given higher explanatory power. The upper and lower bounds and the value of delta obtained using a higher theoretical R-squared provide clearer information on the role of unobservable that overturns the result because higher explanatory power is assumed.

5 | Results

Table 2 provides the proportions of retirement pathways by licensing status from the samples used in competing risk analysis and matching estimations, respectively. For both samples, the proportion of licensed workers who chose "switching occupation" is significantly smaller than that for unlicensed workers. Similarly, the proportion of licensed workers who chose "reducing work hours only" is significantly larger than that for unlicensed workers. These results are consistent with our hypotheses that licensed workers are less likely to choose the pathways that involve the loss of career benefits (i.e., switching occupations) and more likely to choose the pathways that do not involve such losses (i.e., reducing work hours in the same job).

5.1 | Results From Competing Risk Analysis

Table 3 shows the estimations of Equation (1) using clustered competing risk analysis with propensity score matching. Each column shows the SHR and the 95% confidence intervals from the competing risk analysis using the corresponding retirement pathway as a failure outcome, listed at the top of each column. The estimated SHRs for occupational licensing have

TABLE 2 | Proportion of older workers choosing various retirement pathways by licensing status, CPS.

	Competing risk analysis				Matching estimations			
	Unlicensed		Licensed		Unlicensed		Licensed	
Pathways	**Count**	**%**	**Count**	**%**	**Count**	**%**	**Count**	**%**
Switching occupations	327	0.609	71	0.335	299	0.557	75	0.354
Moving to different employers	80	0.149	59	0.278	76	0.142	68	0.321
Reducing work hours only	19	0.035	27	0.127	22	0.041	25	0.118
Both pathways at once	37	0.069	16	0.075	36	0.067	16	0.075
Exit workforce	74	0.138	39	0.184	70	0.130	42	0.198
Subtotal (excluding no change)	537		212		503		226	
No change	885		410		810		448	
Total	1422		622		1313		674	

Note: "No change" comprises the workers who remain in their full-time career job until the end of the survey wave.

TABLE 3 | Clustered competing risk analysis with propensity score matching.

	(1)		(2)		(3)		(4)		(5)	
	Switching occupations		Moving to different employers		Reducing work hours		Two or more pathways at once		Directly exiting the labor force	
	SHR	**95% CI**	**SHR**	**95% CI**	**SHR**	**95% CI**	**SHR**	**95% CI**	**SHR**	**95% CI**
Licensed (1 = Yes)	0.786*	0.646–0.957	1.230	0.911–1.662	3.837***	1.795–8.201	1.295	0.835–2.008	1.203	0.837–1.728
Sex (1 = Female)	1.116	0.886–1.405	1.080	0.740–1.575	1.317	0.721–2.407	0.640	0.344–1.189	1.183	0.733–1.912
Spouse presence (1 = Yes)	1.089	0.898–1.320	1.309	0.958–1.790	2.308**	1.269–4.199	0.833	0.398–1.741	1.094	0.739–1.619
Race (1 = Non-White)	1.354**	1.076–1.704	1.201	0.792–1.822	0.193**	0.070–0.533	0.991	0.529–1.855	1.162	0.674–2.004
Education (1 = Bachelor's or higher)	0.832	0.672–1.032	0.936	0.623–1.406	1.152	0.419–3.167	1.024	0.537–1.955	0.981	0.661–1.455
ln (Weekly earnings)	0.912	0.767–1.085	1.171	0.724–1.895	0.443**	0.264–0.745	0.914	0.432–1.934	1.903**	1.276–2.836
O*NET composite										
Self-direction	0.979	0.957–1.001	1.021	0.978–1.067	0.904	0.813–1.005	0.998	0.921–1.081	1.013	0.961–1.068
Physically hazardous	1.010	0.994–1.025	1.002	0.976–1.028	0.956	0.907–1.008	0.989	0.952–1.026	0.998	0.969–1.028
Physically active	0.998	0.986–1.011	0.996	0.972–1.020	0.958**	0.934–0.983	1.010	0.982–1.038	1.007	0.985–1.031
Care work	1.020	0.997–1.042	0.964	0.921–1.009	1.088	0.980–1.208	1.020	0.948–1.097	0.984	0.935–1.036
Automation and repetition	0.993	0.980–1.007	1.009	0.978–1.041	1.031	0.992–1.071	1.035*	1.002–1.069	1.005	0.977–1.035
No. of respondents choosing following pathway	398		139		46		53		113	
Log-likelihood	−2931.493		−989.931		−267.182		−346.406		−779.703	
Observations	2044		2044		2044		2044		2044	

Note: The table provides sub-distributional hazard ratios (SHR) and their 95% confidence interval (95% CI) from the clustered competing risk analysis with propensity score matching using the IPUMS-CPS, 2017–2023. Because the sample size is insufficient to impose career occupation fixed effects, the Standard Occupational Classification (SOC) groups of career occupations are used for the estimations. In addition to remaining in the career job, the competing risks are (1) switching occupations, (2) moving to different employers, (3) reducing work hours, (4) two or more pathways at once, and (5) directly exiting the labor force. Each estimation is controlled for the SOC group, age of entering the survey, state of residency, and year and month of entering the survey.

*$p < 0.05$.

**$p < 0.01$.

***$p < 0.001$.

the expected values. In the first column, the estimated SHR for licensing status is 0.786 and statistically significant, which implies that licensed workers are less likely than unlicensed workers to choose to switch occupations from their career jobs. In the third column, the estimated SHR is 3.837 and statistically significant, implying that licensed workers are more likely to choose to reduce work hours within the same employers than unlicensed workers. These results support our hypotheses that licensed workers are less likely to choose the pathways that involve the loss of career benefits, while they are more likely to choose the pathways that do not involve such losses. In the second and last columns, the estimated SHRs are not statistically significant, implying weak or no effect of occupational licensing on the choice of corresponding retirement pathways.

While most of the SHRs for the covariates are not statistically significant, the estimated SHR for log-transformed weekly earnings in the third column is 0.443 and statistically significant. This result implies that workers making higher labor income from their career jobs are less likely to reduce their work hours as their retirement pathway. Since the amounts of defined-benefit pensions and Social Security benefits are influenced by the amount of labor income in later work lives,[5] the subsequent reduction in labor income due to work-hour reduction can make the phased retirement option less preferable to high-income earners (Cahill and Quinn 2020).

5.2 | Robustness Check: Results From the Matching Estimates

Table 4 shows the estimates of Equation (2) using the CPS and the matching techniques. Each column shows the estimated coefficients and standard errors from matching techniques using the retirement pathway as a dependent variable, listed at the top of each column. The estimated coefficients have the expected signs. In the first column, the estimated coefficient for licensing status is −0.031 and statistically significant. In other words, licensed workers are 3.1 percentage points less likely than unlicensed workers to switch to different occupations from their career jobs. This result is consistent with the findings in the previous subsection and the results in Kleiner and Xu (2024): Occupational licensing reduces cross-occupational mobility. The third column is again consistent with the previous subsection: The estimated coefficient for licensing status is 0.018 and statistically significant. It implies that licensed workers are more likely to reduce their work hours within the same employer, as their bridge employment is 1.8 percentage points higher than unlicensed workers, which is also consistent with the previous literature (Han and Kleiner 2021).

Consistent with the estimations using the CRA, the estimated coefficient for log-transformed earnings in the third column is negative and statistically significant. This result provides additional evidence that high-income earners are less likely to reduce their work hours later in their work lives.

One concern with the estimations is in Table 4 that the Oster delta is significantly large when R_{max} is assumed to be 1.3 times the R-squared of the full model, implying that the sign of the estimated coefficients is more sensitive to change in the unobservables. One of the reasons for the large delta is the small sample size relative to the number of matching cells. Because individual occupations are used for the matching without coarsening, the number of observations in each matched cell is relatively small, leading to greater sensitivity of the estimated coefficients. To further evaluate the influence of omitted variable bias, we impose higher R_{max} values (0.75 and 1.00) to conduct theoretical regressions.

In the third and fourth rows, for all the estimated coefficients with statistical significance, the Oster lower and upper bounds show that the ranges of estimated coefficients do not include zero, implying that the estimated effects remain statistically significant without changing their signs, assuming the explained variance of the R-squared of 0.75 and even 1.00. Furthermore, the Oster deltas for these coefficients quickly shrink as we impose higher R_{max}, implying a higher possibility that the signs of the estimated coefficients will remain the same even if greater explanatory power is gained. These results also suggest the sensitivity of estimated coefficients could be improved by using larger datasets.

5.3 | Robustness Check: Different Populations of Workers

Although the results in the previous subsections are consistent with previous studies, these also may imply that the influence of occupational licensing in the choice of career transitions is the same across all ages of workers. However, the choices of career transitions have different meanings and outcomes by the age of workers. For instance, moving to different employers is a way of career development for younger workers, and occupational licensing can contribute to this process as a "signal" of higher productivity and commitment to the occupation and jobs (Kleiner 2000; Blair and Chung 2024). However, this is not the case for older workers. In particular, older workers in their FC would not prefer moving to new employers because of the loss of firm-specific human capital and tenure effect; instead, they prefer "phased retirement," discussed in the previous section. In other words, the outcomes of occupational licensing on the choice of career transitions are different by the age of workers.

To examine these differences, we use the sample of younger workers aged between 31 and 43 from the CPS. Note that we do not impose the FC job conditions (i.e., 10+ years of tenure) on younger workers since their duration of labor force participation is significantly shorter than that for older workers. Instead, we subsample the younger workers who have 1+ years of tenure so that we sort out those who made career transitions within a year and therefore have a low chance of making another transition within the given observation period. We use clustered competing risk analysis with propensity score matching to obtain the SHRs and 95% confidence intervals for the failure of interest considering the SHRs of other failures.

Table 5 shows the results from clustered competing risk analysis with propensity score matching using the sample of younger workers. The estimated SHR for licensing status in the first column is 0.733 and statistically significant, implying that

TABLE 4 | Matching estimations—Current Population Survey (CPS).

	(1)	(2)	(3)	(4)	(5)
	Switching occupation	**Moving to different employers**	**Reducing work hours**	**Two or more pathways at once**	**Directly exiting the labor force**
License (1 = Yes)	−0.031*	0.008	0.018*	−0.006	−0.036**
	(0.014)	(0.013)	(0.008)	(0.007)	(0.012)
R_{max}	0.3913	0.3029	0.3159	0.3445	0.3494
(LB, UB)	(−0.033, −0.031)	(0.006, 0.008)	(0.018, 0.019)	(−0.008, −0.006)	(−0.036, −0.029)
Delta	−16.340	3.583	−15.301	−4.441	4.950
$R_{max}=0.75$					
(LB, UB)	(−0.041, −0.031)	(−0.009, 0.008)	(0.018, 0.026)	(−0.015, −0.006)	(−0.036, −0.010)
Delta	−3.322	0.483	−2.275	−0.732	1.345
$R_{max}=1.00$					
(LB, UB)	(−0.047, −0.031)	(−0.017, 0.008)	(0.018, 0.030)	(−0.020, −0.068)	(−0.036, 0.007)
Delta	−2.136	0.325	−1.527	−0.483	0.833
Sex (1 = Female)	0.032	0.0361*	0.002	−0.034***	0.019
	(0.020)	(0.018)	(0.011)	(0.009)	(0.017)
Spouse presence (1 = Yes)	0.043*	0.039*	0.005	0.008	0.019
	(0.018)	(0.016)	(0.009)	(0.008)	(0.015)
Race (1 = Non-White)	0.035	0.070***	−0.017	−0.012	0.022
	(0.022)	(0.021)	(0.012)	(0.011)	(0.019)
Education (1 = Bachelor's or higher)	−0.059*	0.023	−0.004	0.018	0.015
	(0.023)	(0.021)	(0.012)	(0.011)	(0.019)
ln (Weekly earnings)	−0.009	0.059**	−0.032**	−0.018	0.038*
	(0.020)	(0.018)	(0.011)	(0.009)	(0.017)
No. of respondents choosing following pathway	374	144	49	52	147
Observation	1987	1987	1987	1987	1987
R^2	0.301	0.233	0.243	0.265	0.349

Note: The table provides the estimated coefficients and standard errors from propensity score matching using the matched sample of the IPUMS-CPS, 2017–2023. For matching, we use coarsened exact matching. To avoid incidental parameter problems, we use a linear probability model to obtain the propensity of acquiring licenses. The coefficients and standard errors, provided in parentheses, are generated from the propensity score matching estimation using the matched sample, obtained from the coarsened exact matching. Each estimation is controlled for career occupations, age of entering the survey, state of residency, and year and month of entering the survey.

*$p<0.05$.

**$p<0.01$.

***$p<0.001$.

TABLE 5 | Robustness check—clustered competing risk analysis with PSM, younger workers (age 31–43).

	(1)		(2)		(3)		(4)		(5)	
	Switching occupations		Moving to different employers		Reducing work hours		Two or more pathways at once		Directly exiting the labor force	
	SHR	95% CI	SHR	95% CI	SHR	95% CI	SHR	95% CI	SHR	95% CI
Licensed (1 = Yes)	0.733**	0.596–0.901	1.296*	1.052–1.597	0.941	0.681–1.301	0.730	0.493–1.080	1.355	0.873–2.103
Sex (1 = Female)	0.889	0.780–1.012	0.893	0.708–1.127	1.004	0.564–1.789	1.212	0.835–1.759	1.278	0.788–2.074
Spouse presence (1 = Yes)	0.944	0.834–1.069	1.140	0.840–1.546	0.968	0.675–1.390	0.968	0.685–1.369	1.817*	1.033–3.198
Race (1 = Non-White)	1.164*	1.014–1.335	1.072	0.798–1.440	1.398	0.840–2.325	1.577*	1.071–2.322	1.498	0.873–2.569
Education (1 = bachelor's or higher)	0.914	0.789–1.058	1.157	0.865–1.547	0.923	0.534–1.597	0.896	0.604–1.329	0.827	0.490–1.396
ln (Weekly earnings)	0.788***	0.695–0.892	1.041	0.813–1.333	0.576**	0.403–0.824	0.680*	0.476–0.971	0.451**	0.267–0.764
O*NET composite										
Self-direction	1.011	0.998–1.024	1.023	0.982–1.065	0.971	0.926–1.019	1.009	0.974–1.045	0.967	0.902–1.037
Physically hazardous	0.997	0.989–1.005	1.005	0.989–1.021	0.997	0.971–1.024	1.007	0.986–1.028	0.994	0.961–1.028
Physically active	0.999	0.993–1.006	0.985*	0.973–0.997	0.999	0.980–1.018	1.005	0.988–1.023	1.005	0.980–1.030
Care work	0.990	0.978–1.003	0.978	0.938–1.019	1.032	0.979–1.088	0.998	0.965–1.032	1.033	0.959–1.112
Automation and repetition	1.005	0.998–1.011	0.977**	0.963–0.992	0.994	0.965–1.023	0.995	0.977–1.014	0.997	0.975–1.020
No. of respondents choosing following pathway	976		264		109		146		72	
Log-likelihood	−7959.142		−2104.489		−825.142		−1148.592		−525.813	
Observations	4190		4190		4190		4190		4190	

Note: The table provides subdistributional hazard ratios (SHR) and their 95% confidence interval (95% CI) from the clustered competing risk analysis with propensity score matching using the IPUMS-CPS, 2017–2023. Because the sample size is insufficient to impose career occupation fixed effects, the Standard Occupational Classification (SOC) groups of career occupations are used for the estimations. In addition to remaining in the career job, the competing risks are (1) switching occupations, (2) moving to different employers, (3) reducing work hours, (4) two or more pathways at once, and (5) directly exiting the labor force. Each estimation is controlled for the SOC group, age of entering the survey, state of residency, and year and month of entering the survey.

*$p < 0.05$.

**$p < 0.01$.

***$p < 0.001$.

TABLE 6 | Robustness check—clustered competing risk analysis with PSM, older workers with tenure < 10 years.

	(1)		(2)		(3)		(4)		(5)	
	Switching occupations		Moving to different employers		Reducing work hours		Two or more pathways at once		Directly exiting the labor force	
	SHR	95% CI	SHR	95% CI	SHR	95% CI	SHR	95% CI	SHR	95% CI
Licensed (1 = Yes)	0.972	0.757–1.248	0.891	0.619–1.282	0.846	0.471–1.521	Estimation not feasible due to non-symmetric or highly singular variance matrix		1.046	0.604–1.813
Sex (1 = Female)	0.604***	0.473–0.770	1.164	0.644–2.102	1.293	0.600–2.784			1.663	0.997–2.774
Spouse presence (1 = Yes)	1.044	0.820–1.329	1.062	0.551–2.045	0.561	0.304–1.037			0.895	0.559–1.433
Race (1 = Non-White)	1.144	0.850–1.539	1.539	0.848–2.793	1.822	0.782–4.243			2.100	0.995–4.430
Education (1 = Bachelor's or higher)	0.771	0.588–1.010	1.041	0.639–1.695	1.019	0.387–2.683			0.815	0.381–1.745
ln (Weekly earnings)	0.960	0.786–1.172	1.124	0.681–1.854	0.720	0.449–1.154			0.872	0.672–1.132
O*NET composite										
Self-direction	0.997	0.967–1.028	0.965	0.915–1.018	0.981	0.871–1.106			0.947	0.884–1.016
Physically hazardous	1.010	0.994–1.025	1.068***	1.035–1.103	0.965	0.901–1.032			0.954	0.902–1.010
Physically active	1.001	0.986–1.015	0.935***	0.903–0.969	1.059*	1.002–1.120			1.010	0.972–1.049
Care work	0.997	0.963–1.032	1.021	0.967–1.078	0.996	0.881–1.125			1.081*	1.005–1.164
Automation and repetition	1.014	0.993–1.035	0.967	0.931–1.005	1.035	0.980–1.094			1.015	0.954–1.080
No. of respondents choosing following pathway	275		86		39		48		66	
Log-likelihood	−1908.866		−550.661		−221.169		−284.919		−396.549	
Observations	1291		1291		1291		1291		1291	

Note: The table provides subdistributional hazard ratios (SHR) and their 95% confidence interval (95% CI) from the clustered competing risk analysis with propensity score matching using the IPUMS-CPS, 2017–2023. Because the sample size is insufficient to impose career occupation fixed effects, the Standard Occupational Classification (SOC) groups of career occupations are used for the estimations. In addition to remaining in the career job, the competing risks are (1) switching occupations, (2) moving to different employers, (3) reducing work hours, (4) two or more pathways at once, and (5) directly exiting the labor force. Each estimation is controlled for the SOC group, age of entering the survey, state of residency, and year and month of entering the survey.

*$p < 0.05$.

**$p < 0.01$.

***$p < 0.001$.

occupational licensing reduces cross-occupational mobility for younger workers; this result is consistent with the previous studies (Kleiner and Xu 2024). On the other hand, in the second column, the estimated SHR is 1.296 and statistically significant, implying that occupational licensing increases cross-employer mobility among younger workers. This is consistent with the prediction that occupational licensing helps younger workers' career development by signaling their higher productivity and commitment to their occupations and jobs. Furthermore, in the third column, the estimated SHR is not statistically significant, implying that occupational licensing does not influence the choice of work schedule for younger workers; instead, it only affects older workers' choices of work schedule.

One of the important conditions we imposed on the sample of older workers is the "full-time career" job status because we assume that the career benefits, mostly from the accumulation of occupation- and firm-specific human capital and job tenure, are the important factor of older workers' preference for retirement pathways. To validate this assumption, we conduct the same estimations using the sample of older workers (age: 51–63) with less than 10 years of job tenure. Table 6 shows the results from clustered competing risk analysis with propensity score matching using the sample of older workers with less than 10 years of job tenure. The proportions of older workers who made retirement transitions are similar to those of older workers with 10+ years of job tenure across all four pathways. However, the estimated SHRs for licensing status are not statistically significant across all columns, implying a weak or no effect of occupational licensing on the choice of retirement pathways among workers with shorter job tenure. This result is consistent with the theoretical assumption that longer job tenure is associated with career benefits that let the occupational license playing a crucial role in determining older workers' preference for retirement pathways.

6 | Conclusion

We examine the role occupational licensing plays for workers at the end of their work careers by investigating its influence on older workers' choice of retirement pathways. The results from these estimations are consistent with our hypotheses; licensed workers are less likely to choose the pathways that involve the loss of career benefits and more likely to select greater flexibility toward the end of their careers. These results are consistent with the theoretical predictions that licensed workers tend to have higher wages and more benefits and flexibility even toward the end of their careers. These results are from older workers with a significantly longer job tenure (10+ years), suggesting that job tenure is also an important aspect in the choice of retirement pathways. Furthermore, our results show that occupational licensing provides different benefits to licensed workers based on the age of these workers because each type of career transition has different meanings and benefits to workers of different ages. While occupational licensing reduces cross-occupational mobility across all ages, it increases cross-employer mobility among younger workers only. Similarly, it increases the part-time work schedule among older workers only. Occupational licensing generally results in higher wages and benefits, and our estimates suggest that regulated workers have more labor market flexibility regarding hours of work and are less likely to switch occupations in their later work lives. These results are consistent with models that occupational licensing can provide higher compensation through restrictions on labor supply (Kleiner and Soltas 2023).

Retaining older workers is an important human resource issue for businesses and an active research agenda for analysts of labor policy. Phased retirement is an option that allows for retaining older workers and maintaining employees' occupation- and firm-specific human capital while training new workers in the essential operations of the firm. From a business perspective, however, there are several concerns about its feasibility and efficiency (Hutchens 2010). For instance, can two part-time workers perform as well as one full-time worker? Also, will part-time workers exert the same level of work attachment and effort as full-time workers? Our results imply that occupational licensing contributes to older workers' favorable choice of retirement pathways (i.e., phased retirement), since moving into a licensed occupation may reflect a career choice. Still, an employer's support for maintaining licensing status, including occupational training and costs of renewal, will likely contribute to retaining older workers by extending the added commitment to the occupation as well as the firm. Government assistance in maintaining licensing status for self-employed older workers will also contribute to retaining older workers and their human capital in the workforce.

Although we investigate the influence of occupational licensing by utilizing different datasets and methods, there are limitations. The CPS does not provide the reasons for taking bridge employment. The reasons for leaving career jobs, especially the voluntariness of leaving, are important because they are associated with life satisfaction and post-retirement wellbeing (Dingemans and Henkens 2014). We predict that licensed workers are more likely to have control over their retirement transition, but further investigation is needed to confirm this prediction.

Therefore, future research should extend these findings to investigate the degrees of control over the retirement transition by accounting for the voluntariness of leaving career jobs and different retirement pathways. More broadly, how occupational licensing affects these should be studied (Nunn 2018). We also suggest using other econometric approaches, such as the one in Callaway and Sant'Anna (2021), to obtain the effect of occupational licensing on the choice of retirement pathways and duration of labor force participation to further examine the results in the study.

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Data Availability Statement

The data that support the findings of this study are openly available in the IPUMS-CPS at https://cps.ipums.org/cps/.

Endnotes

[1] We exclude the respondents who turned 65 between waves 5 and 8 to avoid the case of respondents becoming eligible for Medicare, because previous studies show that receiving Medicare is one of the strongest drivers of workforce exit (Card, Dobkin, and Maestas 2008; Madrian and Beaulieu 1998).

[2] Some of the variables in the current job tenure supplement were first surveyed in 1983 and then in 1987. These variables have then been collected biannually from 1996 but in February. The current arrangement (biannually in January) started in 2002.

[3] Some of the occupations require attaining a license regardless of the level and region (e.g., medical doctor and pharmacist). Similarly, some of the occupations do not require a license regardless of the level or region. In the data, some of the occupations that require a license in some states do not have an observation of licensed respondents. We exclude the respondents who are in these occupations because we cannot cross-compare the licensed and unlicensed workers in the same occupation.

[4] The survey cohorts are the categories indicating the year and month of entering the CPS, since respondents are surveyed in different time periods. There are three cohorts in the study. For more information, see the section on sample selection and Figure A1.

[5] The amount of defined-benefit pension receipt is based on the labor income from the last several years of working, although it is not a common type of pension nowadays. For Social Security, the labor income from the top 35 earning years is first inflation-adjusted and averaged to obtain the "average indexed monthly earnings." Then, this amount is split into three portions to be weighted and then summed into a final amount. For more information about the calculation of Social Security benefits, see: https://www.ssa.gov/oact/cola/Benefits.html.

[6] For more information about this variable, see the IPUMS-CPS data dictionary: https://cps.ipums.org/cps-action/variables/WKSTAT#description_section.

[7] For more information about the survey questions, see the BLS website: https://www.bls.gov/opub/mlr/2016/article/adding-questions-on-certifications-and-licenses-to-the-current-population-survey.htm.

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Appendix A

CPS Sample Selection and Variable Definitions

Sample Selection

The Current Population Survey (CPS) is a longitudinal survey that follows each survey respondent over 16 months: two 4-month data collections with an 8-month break in between. In this study, two variables are primarily required for the analysis yet are not available every month: weekly labor income and years of tenure. The sample selection and data cleaning are based on the availability of these variables. First, weekly labor income is available for the respondents who were chosen as the Outgoing Rotation Group (ORG); the labor income data are collected in the fourth and eighth waves. Thus, we exclude the respondents who are not in the ORG. Furthermore, we use the labor income from respondents' career jobs to analyze its correlation with the choice of retirement pathway, and therefore, it is important to obtain the weekly earnings from career jobs. To do so, we exclude the respondents who make any work adjustment (switching occupations, moving to different employers, or reducing work hours) in the first four waves.

Second, years of tenure are available in January of every even year in a supplement called the CPS Job Tenure Supplement (JTS). To get the years of tenure for respondents' career jobs, the month of January in even years (2018, 2020, and 2022) must be included in the first four waves. Therefore, we subsample the respondents by the months of entering the survey: October, November, and December in odd years (2017, 2019, and 2021) and January in even years. Then, we separate the respondents into three cohorts by the time of entering the survey: (1) October 2017 to January 2018, (2) October 2019 to January 2020, and (3) October 2021 to January 2022. Since the CPS collects the data in a 16-month duration, the last survey month is April 2023 (16 months from January 2022). Figure A1 provides a visualization of data construction. Since we impose "no bridge employment" in the first four waves, the years of tenure obtained in one of the first four waves determine the respondents' career job tenure. Those whose career job tenure is below 10 years are excluded from the sample.

To define respondents' full-time working conditions, we use the imputed variable of the usual work schedule from the IPUMS-CPS. The variable named *WKSTAT*[6] provides information about the respondent's usual work schedule of the corresponding month—full-time, part-time, unemployed, and not in the labor force—as well as the actual weekly work hours of the month—0, 1–34, and 35+ h. We define respondents' work schedule as full-time if they "usually worked full-time" for at least 2 months during the first four waves. We exclude the respondents who did not keep a full-time work schedule during the first four waves. Since the CPS does not provide historical work data, we cannot observe the actual number of hours worked in the previous 10 years; therefore, we assume that a respondent worked full-time for the previous 10 years if he or she fulfills the above conditions (2+ months of full-time work) in the first four waves.

To obtain the appropriate sample for this study, we impose several conditions for data cleaning. First, we exclude the respondents who were self-employed in one of the first four waves, because the goal of this study is to evaluate the effect of occupational licensing as a fringe benefit from employers in later work lives. Second, we include only the sample of respondents who are non-institutionalized civilians. In other words, we exclude the sample of respondents who have ever served in the armed forces. Third, we exclude the respondents who were either unemployed or not in the labor force at any time in the first four waves.

Defining Retirement Pathways

In this study, we classify bridge employment into three categories: (1) switching occupations, (2) moving to different employers, (3) reducing work hours only, and (4) two or more pathways at once. We define (4) by checking whether a respondent chooses (1), (2), and (3) at the same time.

First, a respondent is defined as "switching occupations" if the respondent moved from his or her career occupation, observed in the first wave, to another occupation that is in a different SOC group from that of the career occupation in between waves 5 and 8 without reducing work hours to part-time in the same wave. Since switching occupations because of promotion cannot be seen as bridge employment, we exclude the changes to the occupations in the SOC group "Management Occupations."

Second, a respondent is defined as "moving to different employers" if he or she answered "no" to the question "Are you still working for the same employer?" in between waves 5 and 8 without reducing work hours to part-time in the same wave. A respondent is also defined as taking this type of bridge employment the respondent's one's worker

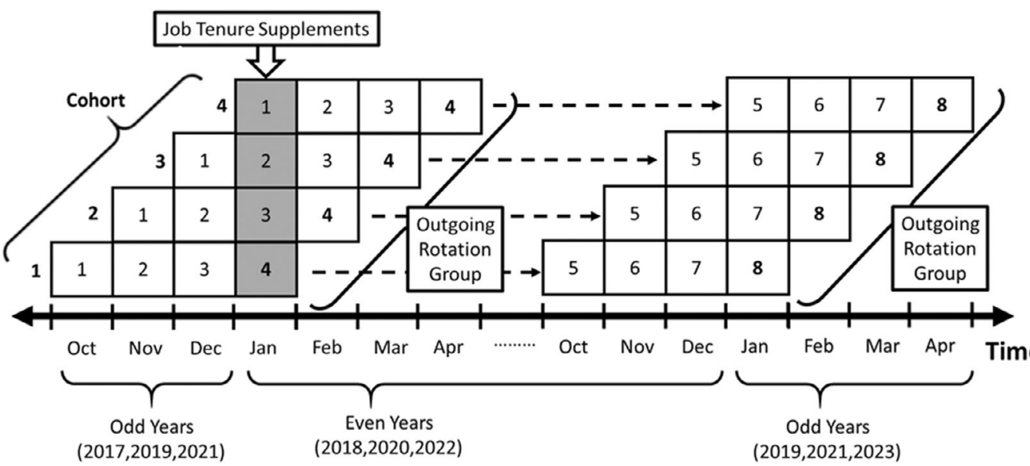

FIGURE A1 | CPS data construction. The numbers in the squares indicate the CPS wave number. Waves 4 and 8 provide the measures of the Outgoing Rotation Group, including hourly wage and weekly earnings. There are a total of three cohorts between 2017 and 2023.

class—self-employed, employed in a private sector, or employed in a public sector—changes in between waves 5 and 8 without reducing work hours to part-time in the same wave.

Third, a respondent is defined as "reducing work hours" if he or she chooses any work schedule options that involve "usually work part-time" or "work part-time for economic or non-economic reasons" for the questions on full- and part-time work status in between waves 5 and 8 without switching occupations or employers in the same wave. To define the work status of respondents, we use the variable *WKSTAT*, which is an imputed variable provided by the IPUMS-CPS that re-coded the respondents' usual work schedule and the reasons. A respondent is also defined as taking this type of bridge employment if the respondent reduced weekly work hours from 35+ h to fewer than 35 h per week between waves 5 and 8.

Last, a respondent is defined as "two or more pathways at once" if the respondent chose two or three pathways in the same wave (between waves 5 and 8).

Defining Occupational Licensing Attainment in the CPS

Below is the description of how active occupational licensing status is defined using the CPS data, and the actual CPS survey questions asked to the respondents.[7] In the non-ASEC CPS survey, respondents aged 16 and older are first asked the following questions:

(1) Do (you/name) have a *currently active* professional certification or a state or industry license? Do *not* include business licenses, such as a liquor license or vending license.

If respondents answered "yes" to this question, then they are asked two additional questions:

(2) Were any of (your/his/her) certifications or licenses issued by the federal, state, or local government?
(3) Earlier you told me (you/name) had a currently active professional certification or license. Is (your/his/her) certification or license required for (your/his/her) (job/main job/job from which [you are/he is/she is] on layoff/job at which [you/he/she] last worked)?

Question (2) determines whether the licenses are issued by the government, ensuring that respondents acquired "a right to practice" from the government. Question (3) ensures that the licensed respondents utilize their "right to practice" in their workplace.

Active occupational licensing status is defined according to questions (2) and (3), since these questions are asked only to the respondents who answered "yes" to question (1). If a respondent answered "yes" to both questions (2) and (3) for at least 2 months during the first four waves, this respondent is defined as holding active occupational licensing status. Otherwise, the respondents do not hold this status.

Appendix B

List of Measures for Occupational Requirements Composite From the Occupational Information Network

Composite	O*NET category	List of measures
Self-direction	Work activities • Mental process ◦ Reasoning and decision-making	1. Organizing, planning, and prioritizing work 2. Thinking creatively 3. Making decisions and solving problems 4. Developing objectives and strategies 5. Scheduling work and activities
	Work context • Interpersonal relationships ◦ Responsibility for others	1. Responsible for outcomes and results
	Work activities • Interacting with others ◦ Coordinating, developing, managing, and advising	1. Coordinating the work and activities of others 2. Guiding, directing, and motivating subordinates
	Work context • Interpersonal relationships ◦ Role relationships ■ Job interactions	1. Coordinate or lead others
Physically hazardous	Work context • Physical work conditions ◦ Job hazards ■ Frequency of exposure to job hazards	1. Exposed to hazardous conditions 2. Exposed to hazardous equipment 3. Exposed to disease or infections 4. Exposed to contaminants 5. Sounds and noise levels are distracting or uncomfortable 6. Very hot or cold temperatures
Physically active	Work context • Physical work conditions ◦ Body positioning ■ Time spent in body positions	1. Spend time walking and running 2. Spend time bending or twisting the body 3. Spend time climbing ladders, scaffolds, or poles 4. Spend time standing 5. Spend time sitting 6. Spend time kneeling, crouching, stooping, or crawling
	Work activities • Work output ◦ Performing physical and manual work activities	1. Performing general physical activities
Interpersonal relations	Work context • Interpersonal relationships ◦ Conflictual contact	1. Deal with unpleasant or angry people 2. Deal with physically aggressive people 3. Frequency of conflict situations
	Work activities • Interacting with others ◦ Communicating and interacting	1. Resolving conflict and negotiating with others
Automation and repetition	Work context • Structural job characteristics ◦ Routine versus challenging work	1. Importance of repeating the same tasks 2. Degree of automation 3. Pace determined by the speed of equipment 4. Spend time making repetitive motions

Note: For more information about each measure, check the Occupational Information Network (O*NET). For more information about the O*NET components for each composite are selected, see the Family Life Project (Crouter et al. 2006).