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ABSTRACT

Ways of leaving the labor force has 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 and Survey of Income and Program Participation to investigate how occupational licensing influences American later-career workers' choice of retirement pathways. Our results show that licensed workers are less likely to choose to change careers but more likely to reduce work hours in transitioning out of the workforce. 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.

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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 number of workers aged 60 and above in the U.S. 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 et al., 2006, 2012, 2018; Geyer and Welteke, 2021; Gustman and Steinmeier, 2000; Ruhm, 1990; 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 U.S. About one in four workers has attained a license from the government, with even more covered by statutes (Gittleman and Kleiner, 2016; Cunningham, 2019). We evaluate how occupational licensing influences the choice of retirement pathways of older workers in the U.S. We use the Current Population Survey (CPS) and the Survey of Income and Program Participation (SIPP) for workers who have attained an occupational license from the government in order to work.

Our paper provides two innovative contributions to literature. First, the study is one of the first to examine the intensive margin benefits of occupational licensing to workers. Previous studies largely cover the extensive margin of the benefits of occupational licensing (e.g., Dillender et al., 2024; Gittleman et al., 2018; Kleiner, 2006; Kleiner and Krueger, 2013; 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' in the retirement transition.

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 (FC), and in contrast to unlicensed employees, licensed workers can choose to reduce work hours toward the end of their careers (Han and Kleiner, 2021). Overall, having an occupational license gives workers greater flexibility and voice within the organization, even at the end of their careers.

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 data sets, 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 of 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 fill in the work gap between career jobs and complete withdrawal from the labor force by adjusting work settings such as occupations, employers, or work hours (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). 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 have 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 et al., 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 to 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 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, developing retirement pathways is relevant in terms of evaluating the economic costs and benefits of different types of bridge employment to reducing labor force participation and hours of work. In this study, we develop a typology by creating two categories of bridge employment. First, "switching occupations/employers" is a move from the occupation of one's career job to another occupation that is not related to promotion or a move from the employer of one's career job to another employer. Second, "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 university admissions officer quitting her job and becoming a part-time massage therapist at a local establishment involves two categories of bridge employment — switching occupations/employers and reducing work hours — at once.

Given the two 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; Topel, 1991). On the other hand, 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 employer. 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 also involves 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 supply and employment, and licensed workers are thereby put in favorable labor market positions in regulated occupations (Blair and Chung, 2022; Kleiner and Soltas, 2023). Previous studies provide evidence that licensed workers tend to receive more fringe benefits such as employersponsored health insurance and job security (Gittleman et al., 2018; Kleiner and Krueger, 2010; 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 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 the 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 use two major government survey data sets that have asked questions on occupational licensing during the last decade. We use the Current Population Survey (CPS) for the main analyses and the Survey of Income and Program Participation (SIPP) for the robustness check. First, we mainly use the IPUMS CPS Outgoing Rotation Group (ORG) from October 2017 to April 2023 to evaluate how occupational licensing influences the choice of retirement pathways. 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

[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 et al., 2008; Madrian and Beaulieu, 1998).

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 the 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 (1,600+ hours annually) for 10+ years in the same job (Cahill et al., 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),

[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.

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 four mutually exclusive categories and use as a quaternary dependent variable, considering the overlaps between two or more types of bridge employment and direct exit from the labor force. First, “switching occupations/employers” is defined as a move to an occupation that is in a different Standard Occupational Classification (SOC) group from the FC occupation and/or a move to an employer that is different from the FC employer without reducing work hours to part-time. We operationalize this category by first defining “switching occupations” and “switching employers” separately and then merging them into one category. To avoid changes in occupation due to promotion, we exclude the switches to the occupations in the SOC group “Management Occupations.” Similarly, to avoid the change in employer for a pay raise, we exclude the respondents whose employer switching involves a rise in

[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.

weekly earnings. Second, “reducing work hours only” is defined as a reduction in weekly hours from full-time to part-time: fewer than 35 hours per week. Third, “both pathways at once” is defined as having bridge employment that involves both switching occupations or employers and reducing work hours at the same time. 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 Reexamining the Workforce Transitions with the Survey of Income and Program Participation (SIPP)

For a robustness check, we use the SIPP 2014 to check the consistency of the estimates with the CPS. The SIPP 2014 is a longitudinal collection of Americans from January 2013 to December 2016, providing a variety of information from demographic and financial variables on the participation of specific government programs. There are two advantages of using the SIPP 2014. First, the 4-year duration of the SIPP 2014 allows for capturing the choice of retirement pathways in a longer time horizon, whereas the CPS has only 16 months of data with 8 months omitted in between. Second, it provides detailed information about work data, including respondents’ first and second jobs and corresponding wages, weekly work hours, occupations, and other information. In this study, we draw a sample of respondents between the ages of 51 and 61[4] who have FC jobs in December 2013.

[4] As with the CPS, we specifically restricted the age of the sample to avoid the case of respondents becoming age 65 before the last wave.

We mostly follow the same definitions and conditions as the CPS, including the definition of FC job, the sample demography, and the categorization of bridge employment. One difference compared with the CPS is that we assume that the workers have active licensing status if they said yes to the questions “has earned a professional certification or license” and “the certification or license issued by federal, state, or local government,” because the SIPP 2014 did not ask whether the respondents’ licenses are required for a job. In addition, “reducing work hours only” is defined as a reduction of work hours from full-time (35+ hours per week) to part-time (<35 hours per week) for reasons other than “less than 35 hours is full-time,” “unemployed or laid off,” or “retired.”

Seam bias is a well-known issue of the SIPP. Unlike the previous SIPP data sets that interviewed the respondents every four months, the SIPP 2014 interviewed the respondents once a year between February and May of the following year. Therefore, the use of the data from the last month of each year is preferred to avoid seam bias. However, some of the important measures cannot be determined if we use the last month of each year only. For instance, we can know whether a respondent left the FC employer only by checking the variable that indicates the change in employer at the month of leaving. Also, more than one category of bridge employment can be chosen within a year, meaning that we cannot differentiate which category of bridge employment was chosen first if we use the last month of each year only. Thus, we use the entire wave to determine the order of retirement pathways, and the other covariates used in matching and robustness checks are from the data of the last month of 2013. For detailed information about the SIPP sample selection and variable definitions, see Appendix B. Table 2 shows the descriptive statistics of the licensed and unlicensed respondents in the SIPP, before and after matching, used in the robustness check.

3.3 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 "occupational switching." 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 "switching occupations/employers and reducing work."

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 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. Second, 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. In addition, we also conduct nearest-neighbor matching as a robustness check to ensure that our findings are consistent with the results from other empirical methods.

4.1 Competing Risk Analysis

To obtain the influence of occupational licensing on the choice of retirement pathways, we use competing risk analysis (CRA). While standard duration analysis methods allow only a single type of failure as a terminal outcome, CRA allows multiple terminal outcomes (i.e., two or more types of failure) to be estimated using a set of covariates on the marginal probability function (Fine and Gray, 1999). By setting a failure of interest, CRA calculates the sub-distributional hazard ratio for the failure of interest considering the sub-distributional hazards of other failures. 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 sub-distributional hazards 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; this is especially important in the estimation using the SIPP, because it covers a longer time horizon (four years) than the CPS (one year and four months).

In addition to licensing status in the estimation, we introduce socioeconomic and demographic variables including age, sex, spouse presence, race, education, weekly earnings, FC occupations, state of residency, and survey cohorts.[5] The estimation model is

$$\text{Prob}(Y_i = R) = \alpha + \delta L_i + \mathrm{X_i}\beta + \varepsilon_i, \tag{1}$$

where R is the choice of a certain retirement pathway, L_i is the occupational licensing status, and $\mathrm{X_i}$ is the vector of socioeconomic and demographic variables.

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 and SIPP, 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 data sets 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 out 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 is evaluated by job analysts and is used in research to quantitatively represent

[5] 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 12 cohorts in the study. For more information, see the section on sample selection and Figure A1 in Appendix A.

occupational requirements (e.g., Light and McGee, 2015; Speer, 2017). 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 hazard 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 on the process of retirement transitions (e.g., Froidevaux et al., 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 (see, e.g., Consoli et al., 2023). Detailed information about the measures used for each composite is provided in Appendix C.

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 et al., 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

$$\mathrm{P}(Y_i = R) = a + \gamma L_i + \mathrm{M_i}\eta + \overline{\mathrm{X}}_{\mathrm{i}}\mathrm{b} + \varepsilon_i, \tag{2}$$

where R is the choice of a certain retirement pathway, L_i is the occupational licensing status, and $\mathrm{M_i}$ is the vector of variables used for matching, and $\overline{\mathrm{X}}_{\mathrm{i}}$ 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 et al., 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

Tables 3 and 4 provide the proportions of retirement pathways by licensing status using unmatched and matched samples[6] from the CPS and SIPP, respectively. In Table 3, the proportion of licensed workers who chose "switch occupation/employer" is significantly smaller than that for unlicensed workers. Similarly, the proportion of licensed workers who chose "reduce work hours only" is significantly larger than that for unlicensed workers. These trends are consistent in Table 4 as well. These results are consistent with our hypotheses that licensed workers are less likely to

[6] The unmatched sample is the data of respondents used in the competing risk analysis, and the matched sample is the data of respondents used in the matching techniques, sorted using coarsened exact matching and propensity score matching.

choose the pathways that involve the loss of career benefits (i.e., switching occupations/employers) and more likely to choose the pathway that does not involve such losses (i.e., reducing work hours in the same job).

5.1 Results from the Competing Risk Analysis

Table 5 shows the estimations of Equation (1) using CPS and competing risk analysis. Each column shows the estimated sub-distributional hazard ratios (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 SHR for occupational licensing have the expected values. In the first column, the estimated SHR for licensing status is .775 and statistically significant, which implies that licensed workers are less likely than unlicensed workers to choose to switch occupations or employers from their career jobs. In the fourth column, the estimated SHR is 2.547 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 pathway that does not involve such losses. In the last three columns, the estimated SHR and 95% confidence intervals are not provided, because convergence is not achieved owing to the insufficient number of respondents who choose both pathways at once.

Table 6 shows the estimates of Equation (1) using the SIPP and the competing risk analysis. Although one of them is not statistically significant at a 95% confidence level, the estimated SHRs for occupational licensing have the expected signs, consistent with the findings in Table 5. The estimated SHR for licensing status in the first column is .943, and that in the fourth column is 1.277. These results partly support the findings from Table 5 that licensed workers are less likely to switch occupations or employers and more likely to choose phased retirement as their retirement pathway than unlicensed workers, which is consistent with our hypotheses. On the other hand, the estimated SHRs for licensing status in the seventh column, which shows the results for both pathways at once, is not statistically significant.

While most of the SHRs for the covariates are not statistically significant, the estimated SHRs for log-transformed weekly earnings in the fourth column in both tables are below 1.0 and statistically significant (.396 and .713 for Tables 5 and 6, respectively). These results imply 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,[7] 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 Results from the Matching Estimates

Table 7 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 -.039, and it is statistically significant. In other words, licensed workers are 3.9 percentage points less likely than unlicensed workers to switch to different occupations or employers from

[7] 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.

their career jobs, which is consistent with the findings in the previous subsection and the results in Kleiner and Xu (2024). The second column is again consistent with the previous subsection: the estimated coefficient for licensing status is .021, and it is statistically significant. It implies that licensed workers are more likely to reduce their work hours within the same employer, as their bridge employment is 2.1 percentage points higher than unlicensed workers', which is also consistent with the previous literature (Han and Kleiner, 2021).

Table 8 shows the estimates of Equation (2) using the SIPP and matching estimations. The results in this table are again consistent with the findings in the previous subsection. In the first column, the estimated coefficient for licensing status is -.051 and statistically significant, supporting the other findings. According to this column, licensed workers are less likely than unlicensed workers to switch to different occupations or employers from their career jobs by 5.1 percentage points. The estimated coefficient for licensing status in the third column is .034, and it is statistically significant, implying that licensed workers are 3.4 percentage points more likely than unlicensed workers to reduce their work hours within the same employer.

Consistent with the estimations using the CRA, the estimated coefficient for log-transformed earnings in the second column of Table 7 is negative and statistically significant. These results suggest that high-income earners are less likely to reduce their work hours later in their work lives. On the other hand, the estimated coefficients for race are statistically significant for all three columns in Table 8; while non-White older workers are more likely to choose switching occupations/employers and both pathways at once, they are less likely to choose reducing work hours. Previous studies found an association between race and ethnicity and the types of bridge employment (Carr et al., 2021), but further investigation is needed to examine the causal relationship between the workers' socioeconomic characteristics and the types of bridge employment.

One concern with the estimations in Tables 7 and 8 is 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 (.75 and 1.00) to conduct theoretical regressions.

In Tables 7 and 8, for all the estimated coefficients with statistical significance, the Oster lower and upper bounds show that the range of estimated coefficients does not include zero, implying that the estimated effects remain statistically significant without changing their signs, assuming the explained variance of the R-squared of .75 and even 1.00. Furthermore, the Oster deltas for these coefficients quickly shrink as we impose higher R_{Max}. Although some of the values of the Oster delta are relatively high, the Oster bounds still present the possibility that the signs of the estimated coefficients will remain the same, even if greater explanatory power is gained. They also suggest the sensitivity of estimated coefficients could be improved by using larger data sets.

5.3 Robustness Checks

In addition to competing risk analysis and matching estimations, we conduct nearest-neighbor matching as a robustness check. As in the matching estimations, we match licensed and unlicensed workers; we first exactly match these workers by career occupations, and then nearest-neighbor match them by sex, spouse presence, race/ethnicity, education level, and log-transformed weekly earnings. We use Euclidean distance metrics to obtain the average treatment effect on the treated (ATET) of occupational licensing on the choice of retirement pathways. Note that we do not need a large-sample bias adjustment, because we have only one continuous variable (log-transformed weekly earnings) for nearest-neighbor matching; this bias adjustment is needed only if two or more continuous measures are used in matching (Abadie and Imbens, 2006, 2011).

Tables 9 and 10 present the results from nearest-neighbor matching using the CPS and the SIPP, respectively. In both tables, the estimated coefficients in the second column are positive and statistically significant, implying that licensed workers are more likely than unlicensed workers to choose the "reducing work hours" pathway. In Table 9, although not statistically significant in the 95% confidence level, the estimated coefficient in the first row shows that licensed workers are less likely to choose "switching to different occupations or employers."

In summary, the results across all the estimates show that licensed workers are less likely to choose the pathways that involve the loss of career benefits (i.e., switching occupations/employers) and more likely to choose the pathways that do not (i.e., reducing work hours in the same job). These findings are consistent with the hypotheses we proposed that licensed workers get not only higher wages but also additional benefits and flexibility to work at the end of their careers, because they receive more benefits in the form of preferable retirement options. On the other hand, the estimated effects of occupational licensing on choosing both pathways at once are not statistically significant. Providing theoretical implications of this pathway is difficult because the entanglement between each category of bridge employment intertwines the purposes and outcomes. We suggest that future research should attempt to investigate how labor market institutions and regulations can influence the choice of pathways between the categories of bridge employment.

6 Conclusion

We examine the role occupational licensing plays for workers at the end of their work careers. We use two different data sets and two different methods to investigate the influence of occupational licensing 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. 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.

Retaining older workers is an important human resource issue for business 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. 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 data sets and methods, there are limitations. The CPS does not provide the reasons for taking bridge employment, and the SIPP is limited in accounting for them because of the insufficient sample size, although there are questions asking about the reasons for leaving FC employers and reducing work hours. The reasons for leaving career jobs, especially the voluntariness of leaving, are important because they are associated with life satisfaction and post-retirement well-being (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.

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Table 1. Descriptive Statistics - Current Population Survey (CPS)

	Unlicensed Workers				Licensed Workers			
	Unmatched		Matched		Unmatched		Matched	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Observation	1,305		593		888		552	
Switching Occupations/Employers	.270	.444	.239	.427	.160	.367	.154	.361
Reducing Work Hours	.018	.132	.024	.152	.046	.209	.040	.196
Two or More Pathways at Once	.005	.068	.006	.075	.003	.058	.004	.060
Weekly Earning (US$)	1,417	743	1,629	735	1,504	709	1,592	725
Sex (1=Female)	.429	.495	.391	.488	.511	.500	.504	.500
Spouse Present	.736	.441	.756	.430	.745	.436	.743	.438
Race (1=Non-White)	.130	.337	.111	.315	.137	.344	.130	.337
Education (1=HS Grad or Higher)	.961	.194	.971	.169	.978	.147	.978	.146
Age	56.8	3.6	56.9	3.6	56.7	3.7	56.7	3.7

Note: Obtaining matched sample by licensing status is done using coarsened exact matching. The variables used for matching include sex, spouse presence, race, education, weekly earnings, and occupation. Unmatched samples are used in the competing risk analysis, and the matched samples are used in the propensity score matching estimation.

Table 2. Descriptive Statistics - Survey of Income and Program Participation (SIPP)

	Unlicensed Workers				Licensed Workers			
	Unmatched		Matched		Unmatched		Matched	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Observation	1,179		915		421		382	
Switching Occupations/Employers	.299	.458	.348	.476	.228	.420	.267	.443
Reducing Work Hours	.054	.227	.014	.118	.107	.309	.042	.201
Two or More Pathways at Once	.023	.150	.017	.131	.026	.160	.016	.125
Weekly Earning (US$)	1,170	934	1,157	879	1,370	993	1,294	1,000
Sex (1=Female)	.465	.499	.428	.495	.558	.497	.505	.501
Spouse Present	.331	.471	.299	.458	.304	.461	.262	.440
Race (1=Non-White)	.260	.439	.232	.422	.190	.393	.175	.381
Education (1=HS Grad or Higher)	.929	.257	.949	.221	.981	.137	.984	.125
Age	55.8	3.1	55.4	2.9	55.8	3.1	55.6	2.8

Note: Obtaining matched sample by licensing status is done using the coarsened exact matching. The variables used for matching include sex, spouse presence, race, education, weekly earnings, and occupation. Unmatched samples are used in the competing risk analysis, and the matched samples are used in the propensity score matching estimation.

Table 3. Proportion of Older Workers Choosing Retirement Pathways by Licensing Status, CPS

Pathway	Unmatched Sample				Matched Sample			
	Unlicensed		Licensed		Unlicensed		Licensed	
	Count	%	Count	%	Count	%	Count	%
Switch Occupation/Employer	352	77.9	95	58.6	212	72.6	85	57.8
Reduce Work Hours Only	23	5.1	27	16.7	21	7.2	22	15.0
Both Pathways at Once	6	1.3	2	1.2	5	1.7	2	1.4
Exit Workforce	71	15.7	38	23.5	54	18.5	38	25.9
Total (excluding No Change)	452		162		292		147	
No Change	853		431		596		405	
Total	1,305		593		888		552	

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

Table 4. Proportion of Older Workers Choosing Retirement Pathways by Licensing Status, SIPP

Pathway	Unmatched Sample				Matched Sample			
	Unlicensed		Licensed		Unlicensed		Licensed	
	Count	%	Count	%	Count	%	Count	%
Switch Occupation/Employer	342	73.7	94	57.0	318	84.6	102	73.4
Reduce Work Hours Only	56	12.1	38	23.0	13	3.5	16	11.5
Both Pathways at Once	27	5.8	11	6.7	16	4.3	6	4.3
Exit Workforce	39	8.4	22	13.3	29	7.7	15	10.8
Total (excluding No Change)	464		165		376		139	
No Change	683		241		539		243	
Total	1,147		406		915		382	

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

Table 5. Competing Risk Analysis, Current Population Survey (CPS)

	Switching Occupation / Employer			Reducing Work Hours Only			Both Pathways at Once	
	(1)			(2)			(3)	
	SHR	95% CI		SHR	95% CI		SHR	95% CI
Licensed (1=Yes)	.775*	.610	.984	2.547*	1.147	5.660		
Sex (1=Female)	1.043	.855	1.273	1.106	.504	2.426		
Spouse Presence (1=Yes)	1.088	.894	1.324	2.403	.956	6.040		
Race (1=Non-White)	1.210	.952	1.540	.153*	.027	.872		
Education (1=HS Grad or Higher)	1.090	.715	1.662	3.890	.140	107.8	Convergence not achieved,	
ln(Weekly Earning)	.956	.791	1.155	.396**	.225	.699	because there are only 8	
O*NET Composite							respondents that chose	
Self-Direction	.973*	.950	.995	.961	.857	1.078	corresponding pathway	
Physically Hazardous	1.010	.997	1.023	.949	.894	1.007		
Physically Active	.998	.987	1.008	.967	.928	1.009		
Care Work	1.025*	1.001	1.049	1.039	.925	1.168		
Automation & Repetition	.997	.984	1.010	1.018	.971	1.067		
# of Respondents Choosing Following Pathway	447			50			8	
Log-Likelihood	-3,285.732			-297.334			N/A	
Wald Chi^2(102)	218.01			16,884.53			N/A	
Observations	1,898			1,898			1,898	

Note: The table provides sub-distributional hazard ratios (SHR) and their 95% confidence interval (95% CI) from the competing risk analysis 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/employers, (2) reducing work hours only, (3) two or more pathways at once, and (4) 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<.001, ** p<.01, * p<.05.

Table 6. Competing Risk Analysis, Survey of Income and Program Participation (SIPP)

	Switching Occupations / Employer			Reducing Work Hours Only			Both Pathways at Once		
	(1)			(2)			(3)		
	SHR	95% CI		SHR	95% CI		SHR	95% CI	
Licensed (1=Yes)	.943	.748	1.188	1.277	.830	1.965	1.093	.419	2.848
Sex (1=Female)	.684***	.552	.847	1.889*	1.120	3.186	8.859***	2.783	28.20
Spouse Presence (1=Yes)	.962	.792	1.168	.952	.625	1.450	.354**	.162	.771
Race (1=Non-White)	1.143	.921	1.419	.717	.417	1.234	2.889*	1.074	7.772
Education (1=HS Grad or Higher)	.915	.655	1.280	2.858	.670	12.18	.414	.141	1.218
ln(Weekly Earning)	.893	.782	1.020	.713*	.524	.970	1.266	.532	3.016
O*NET Composite									
Self-Direction	1.002	.980	1.025	1.041	.989	1.095	.987	.915	1.064
Physically Hazardous	1.012	.999	1.025	1.004	.976	1.033	1.001	.950	1.054
Physically Active	1.005	.995	1.016	.998	.977	1.019	1.011	.972	1.052
Care Work	.990	.967	1.014	.970	.917	1.027	1.008	.932	1.091
Automation & Repetition	.987*	.976	.999	.999	.977	1.023	.985	.941	1.031
# of Respondents Choosing Following Pathway	449			109			38		
Log-Likelihood	-3,191.203			-712.389			-229.370		
Wald Chi^2(92)	3,82.03			39,948.44			12,801.32		
Observations	1,600			1,600			1,600		

Note: The table provides sub-distributional hazard ratios (SHR) and their 95% confidence interval (95% CI) from the competing risk analysis using the SIPP 2014. 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/employers, (2) reducing work hours only, (3) two or more pathways at once, and (4) directly exiting the labor force. Each estimation is controlled for the SOC group, age of entering the survey, and state of residency. *** p<.001, ** p<.01, * p<.05.

Table 7. Matching Estimations - Current Population Survey (CPS)

	Switching Occupations / Employer	Reducing Work Hours Only	Both Pathways at Once
	(1)	(2)	(3)
License (1=Yes)	-.039*	.021*	-.004
	(.020)	(.009)	(.004)
R_{Max}	.341	.257	.287
(LB,UB)	(-.042, -.039)	(.021, .022)	(-.004, -.004)
Delta	-17.31	-25.28	-11.926
R_{Max} =.75			
(LB,UB)	(-.056, -.039)	(.021, .031)	(-.007, -.004)
Delta	-2.853	-2.856	-1.513
R_{Max} =1.00			
(LB,UB)	(-.065, -.039)	(.021, .037)	(-.008, -.004)
Delta	-1.890	-1.970	-1.208
Sex (1=Female)	-.020	.017	-.004
	(.027)	(.013)	(.005)
Spouse Presence (1=Yes)	.055*	.008	-.010*
	(.024)	(.012)	(.005)
Race (1=Non-White)	.060	-.017	.003
	(.031)	(.015)	(.006)
Education (1=High School Graduate or Higher)	-.038	.097**	-.019
	(.074)	(.035)	(.014)
ln(Earning)	.014	-.057***	.001
	(.031)	(.015)	(.006)
# of Respondents Choosing Following Pathway	297	43	7
Observation	1,440	1,440	1,440
R^2	.262	.198	.221

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<.001, ** p<.01, * p<.05.

Table 8. Matching Estimations - Survey of Income and Program Participation (SIPP)

	Switching Occupations / Employer	Reducing Work Hours Only	Both Pathways at Once
	(1)	(2)	(3)
License (1=Yes)	-.051*	.034***	.007
	(.024)	(.009)	(.007)
R_{Max}	.3692	.2119	.2444
(LB,UB)	(-.052,-.051)	(.033,.034)	(.007,.008)
Delta	62.532	22.022	-7.292
R_{Max} =.75			
(LB,UB)	(-.052,-.051)	(.024,.034)	(.007,.020)
Delta	11.738	2.194	-.733
R_{Max} =1.00			
(LB,UB)	(-.053,-.051)	(.018,.034)	(.007,.028)
Delta	7.655	1.547	-.507
Sex (1=Female)	-.092**	.000	.031**
	(.034)	(.012)	(.009)
Spouse Presence (1=Yes)	-.045	.014	-.016
	(.031)	(.011)	(.008)
Race (1=Non-White)	.094**	-.028*	.024*
	(.035)	(.013)	(.010)
Education (1=High School Graduate or Higher)	-.113	-.015	.004
	(.101)	(.037)	(.028)
ln(Earning)	-.001	-.002	-.002
	(.008)	(.003)	(.002)
# of Respondents Choosing Following Pathway	420	29	22
Observation	1,297	1,297	1,297
R^2	.284	.163	.188

Note: The table provides the estimated coefficients and standard errors from propensity score matching using the matched sample of the SIPP 2014. 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, and state of residency. *** p<.001, ** p<.01, * p<.05.

Table 9. Robustness Check – Nearest Neighbor Matching Using CPS

	Switching Occupations / Employers	Reducing Work Hours Only	Both Pathways at Once
License (1=Yes)	-.053	.031*	-.002
	(.029)	(.014)	(.005)
# of Respondents Choosing Following Pathway	305	40	6
Observation	1,405	1,405	1,405

Note: The estimated coefficients and Abadie-Imbens standard errors, provided in parentheses, are generated from nearest-neighbor matching with Euclidean distance metrics by licensing status. The licensed and unlicensed workers are first exactly matched by occupation and then nearest-neighbor matched using sex, spouse presence, race/ethnicity, education level, and log-transformed weekly earnings. *** p<.001, ** p<.01, * p<.05.

Table 10. Robustness Check – Nearest Neighbor Matching Using SIPP

	Switching Occupations / Employers	Reducing Work Hours Only	Both Pathways at Once
License (1=Yes)	-.018 (.046)	.035** (.013)	-.003 (.012)
# of Respondents Choosing Following Pathway	327	31	19
Observation	1,077	1,077	1,077

Note: The estimated coefficients and Abadie-Imbens standard errors, provided in parentheses, are generated from nearest-neighbor matching with Euclidean distance metrics by licensing status. The licensed and unlicensed workers are first exactly matched by occupation and then nearest-neighbor matched using sex, spouse presence, race/ethnicity, education level, and log-transformed weekly earnings. *** p<.001, ** p<.01, * p<.05.

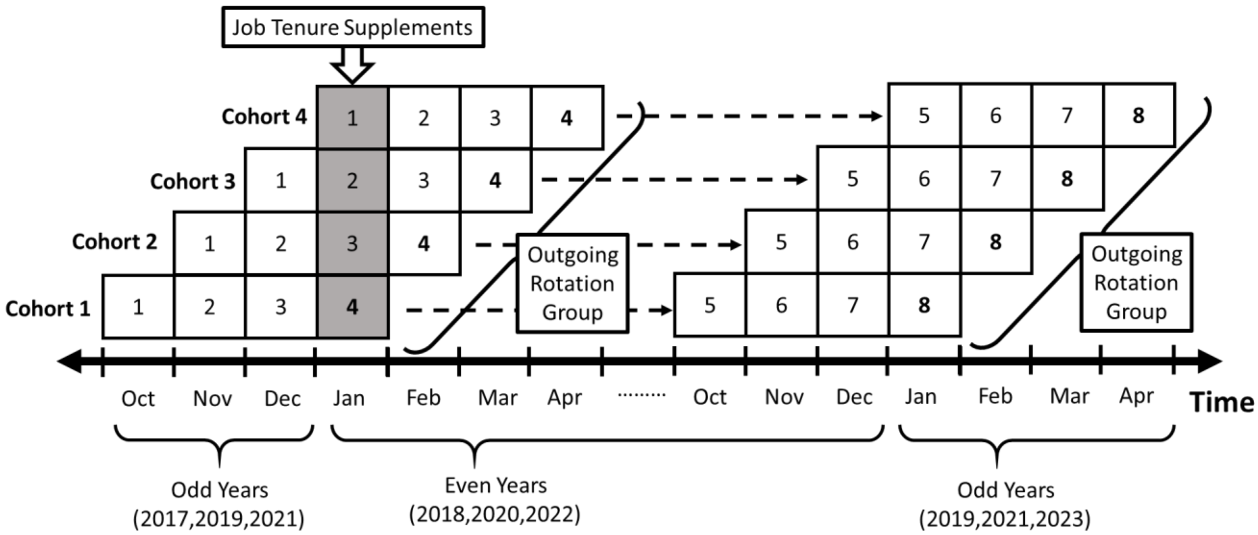
Appendix A. CPS Sample Selection and Variable Definitions

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 is 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, leaving career job 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 job, 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 groups (4 cohorts in each group, a total of 12 cohorts) by the time of entering the survey: (1) October 2017–January 2018, (2) October 2019–January 2020, and (3) October 2021–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.

Figure A1. CPS Data Construction



Note: 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 total of 12 cohorts, 4 cohorts per two years between 2017 and 2023.

To define respondents' full-time working condition, we use the imputed variable of the usual work schedule from the IPUMS-CPS. The variable named *WKSTAT*[8] 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 hours, 1–34 hours, and 35+ hours. We define respondents' work schedule as full-time if they "usually worked full-time" for at least two months during the first four waves. We exclude the respondents who did not keep 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

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

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/employers, (2) reducing work hours only, and (3) both pathways at once. We define (1) by first defining "switching occupations" and "switching employers" separately and then merging them into one category. We define (3) by checking whether a respondent chooses (1) and (2) 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 to 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 "switching full-time career (FC) job employers" if he or she answered "no" to the question "are you still working for the same employer?" in between waves 5 to 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 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 only" 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+ hours to fewer than 35 hours per week in between waves 5 and 8.

Last, a respondent is defined as "both pathways at once" if the respondent reduced work hours to part-time and switched occupations or employers in the same wave (in between wages 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.[9] 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.

[9] 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.

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 two 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. SIPP Sample Selection and Variable Definitions

Sample Selection

Unlike the CPS, the Survey of Income and Program Participation (SIPP) 2014 has all the necessary variables across the waves. However, the existence of seam bias introduces measurement errors into the estimates, since the SIPP 2014 interviewed the respondents once a year between February and May of the following year. To avoid this issue, we mainly use the data from the last month of 2013, except for defining the timing of bridge employment.

One of the main differences between the SIPP and the CPS is that the SIPP 2014 provides detailed information about respondents' jobs; it provides up to seven different jobs that respondents had. In this study, we use the first two reported jobs (for simplicity, we name them jobs A and B) and find the respondent's career jobs based on their weekly work hours and earnings. If a respondent spent more hours on job A than job B in the last month of 2013, then we define job A as the respondent's career job, and vice versa. If a respondent spent the same number of hours in each job, then we compare the weekly earnings from these jobs. If in the last month of 2013, the weekly earnings from job A are higher than those from job B, then we define job A as the respondent's career job, and vice versa.

To define the full-time career (FC) job condition, we mainly use two sets of variables. First, we calculate the years of tenure in the career job by subtracting between 2013 and the year a respondent started working in the main job, observed in the last wave of 2013. We exclude the respondents whose years of tenure in the career job is fewer than 10 years. Second, we calculate the approximate annual work hours by aggregating each month's weekly work hours and then multiplying by 4. On the other hand, some jobs have full-time work that involves fewer than 35 hours per week.[10] We exclude the respondents whose approximate annual work hours are below 1,600 and whose jobs have full-time work that involves fewer than 35 hours a week in the last wave of 2013.

Defining Retirement Pathways

As mentioned above, in this study, we classify bridge employment into three categories: (1) switching occupations/employers, (2) reducing work hours only, and (3) both pathways at once. Following the same classification strategy used for the CPS, we define (1) by first defining "switching occupations" and "switching employers" separately and then merging them into one category. We define (3) by checking whether a respondent chooses (1) and (2) 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 13 and 48 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 "switching full-time career (FC) job employers" if he or she answered one of the following questions:

(1) What is the main reason stopped working for an employer?

(2) What is the main reason gave up or ended this business?

[10] The SIPP provides a set of variables (EJBm_PTRESNn) indicating the reasons why a respondent worked fewer than 35 hours per week. The letter *m* in the variable indicates the job number (from 1 to 7), and *n* indicates the reason's number (from 1 to 3). For more information, see the SIPP Codebook: https://www.census.gov/data-tools/demo/uccb/sippdict?s_keyword=ptresn.

The respondent must also have non-zero weekly work hours in between waves 13 and 48 without reducing work hours to part-time in the same wave. A respondent is also defined as taking this type of bridge employment if the respondent's worker class (which the SIPP 2014 calls "job arrangement")—self-employed, employed in a private sector, or employed in a public sector—changes and has non-zero weekly work hours in between waves 13 and 48 without reducing work hours to part-time in the same wave.

Third, a respondent is defined as "reducing work hours only" if in between waves 13 and 48, he or she chose any answer to the question "What is the main reason you worked less than 35 hours per week?" except "full-time work week is less than 35 hours" and "temporarily unable to work full-time" without switching occupations or leaving a career job employer in the same wave.

Last, a respondent is defined as taking "both pathways at once" if a respondent reduced work hours to part-time and switched occupations or employers in the same wave (in between waves 13 and 48).

Defining Occupational Licensing Attainment in the SIPP

Below is the description of how active occupational licensing status is defined using the SIPP data and the survey questions asked to the respondents.[11] Respondents who are at least 18 years old or whose education level is at or above high school graduate are first asked:

- Has...earned a professional certification or license?

If respondents answered "yes" to this question, then they are asked a question about where they acquired their licenses:

[11] For more information about the questions, see the SIPP Codebook: https://www.census.gov/data-tools/demo/uccb/sippdict?s_keyword=ewhocert.

- Certification or license issued by (2) federal, state, or local government, (3) professional or trade association, (4) business or company, or (5) other group or organization.

Since the government covers “the right to practice” by statute, a respondent is defined as holding active occupational licensing status if he or she selected (2). Unlike the CPS, the SIPP 2014 did not ask questions about whether their licenses are required for jobs. Although the SIPP 2008 asked this question, we use the SIPP 2014 to compare the respondents in the same time as those in the CPS 2016–2023. Thus, we assume that respondents hold active occupational licensing status if they are in their full-time career jobs and acquired licenses from federal, state, or local government in the last month of 2013.

Appendix C. 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

Appendix C Continued

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).