Article

Sociological Methods & Research
1-34

DOI: 10.1177/0049124117729697
journals.sagepub.com/home/smr
SAGE

# Causal Effects of the Timing of Life-course Events: Age at Retirement and Subsequent Health

**N. Barban[1,2], X. de Luna[3], E. Lundholm[4,5], I. Svensson[3] and F. C. Billari[6]**


## Abstract

In this article, we combine the extensive literature on the analysis of life-course trajectories as sequences with the literature on causal inference and propose a new matching approach to investigate the causal effect of the timing of life-course events on subsequent outcomes. Our matching approach takes into account pre-event confounders that are both time-independent and time-dependent as well as life-course trajectories. After matching, treated and control individuals can be compared using standard statistical tests or regression models. We apply our approach to the study of the consequences of the age at retirement on subsequent health outcomes, using a unique data set from Swedish administrative registers. Once selectivity in the timing of retirement is taken into account, effects on hospitalization are small, while early retirement has negative effects on survival. Our


[1] Department of Sociology, University of Oxford, Oxford, United Kingdom
[2] Nuffield College, University of Oxford, Oxford, United Kingdom
[3] Department of Statistics, USBE, Umeå University, Umea, Sweden
[4] Department of Geography and Economic History, Umeå University, Umea, Sweden
[5] Centre for Demographic and Ageing Research (CEDAR), Umeå University, Umea, Sweden
[6] Department of Policy Analysis and Public Management and DONDENA, Bocconi University, Milan, Italy

**Corresponding Author:**
N. Barban, Department of Sociology and Nuffield College, University of Oxford, Manor Road, Oxfordshire, OX1 3UQ Oxford, United Kingdom.
Email: nicola.barban@sociology.ox.ac.uk

approach also allows for heterogeneous treatment effects. We show that the effects of early retirement differ according to preretirement income, with higher income individuals tending to benefit from early retirement, while the opposite is true for individuals with lower income.

**Keywords**

life-course analysis, matching, propensity score, retirement, register data, sequence analysis

What are the consequences of the timing of life-course events? This is a common social science question and methodological challenge. The timing of events is itself a consequence of what has cumulated, in life, up to these events. Previous life-course background and experiences could affect both the timing of events and what happens after the events. In this article, we present a new approach to the estimation of the causal effect of the timing of a life-course event on subsequent outcomes. This approach takes into account individual trajectories prior to the events. To do so, we combine the extensive literature on the analysis of life-course trajectories with the literature on causal inference. We propose a new matching approach and apply it to the estimation of the causal effect of age at retirement on later health outcomes, using novel register data from Sweden. Standard matching estimators based on propensity scores (Rosenbaum and Rubin 1983) pair each treated individual with a single (or multiple) nontreated individual based on a set of observed characteristics. We show that the selection into early retirement (our "treatment" factor) is affected by the trajectories of a set of observed characteristics before treatment.

When studying individual lives, a now common way to make sense of them is to analyze and summarize the whole trajectory of events experienced and states visited, with their timing and sequencing. This is the basic idea behind sequence analysis (Aisenbrey and Fasang 2010a), as well as the formal approach to event history analysis, based on counting processes (Andersen et al. 2012). We use sequence analysis based on optimal matching (OM; Abbott 1995) to develop a matching procedure based on pretreatment trajectories. More specifically, our method develops an extension of nearest neighbor matching estimators to OM distances. Our approach allows, for instance, to match "treated" and "control" individuals who have the most similar health trajectories before retirement. We also combine matching on trajectories with a standard propensity score and develop a combined measure of dissimilarity among individuals.

Our analyses utilize population-wide administrative and health record–linked register data. Our research design allows to have access to a rich set of individual socioeconomic and health characteristics and to follow longitudinally cohorts born from 1935 to 1946, from birth to retirement and beyond. Sweden is a crucial case in the study of the effect of changes in retirement patterns, as it was one of the first countries to introduce flexible retirement and to allow workers to decide at what age to retire (Palmer 2000; Palme et al. 1999). We use hospitalization and mortality as key measures of health outcomes. We conduct separate analysis for different ages at retirement, and we focus in particular on early retirement, defined here as retirement between the ages of 60 and 64.

Our results confirm that early retirement is associated with poorer health outcomes, that is, with higher hospitalization and lower survival rates. However, those who retire early tend to experience worse preretirement health trajectories (hospitalization patterns and trends) with respect to those who retire later. Once we control for preretirement health trajectories and other potential confounding factors, the negative effects of retirement on hospitalization are reduced. We therefore show that standard regression-based estimators of retirement effects on health outcomes tend to overestimate the magnitude of the causal effect of the timing of retirement. For what concerns survival, even after controlling for selection, early retirement has negative effects. We then investigate the heterogeneity of retirement effects, that is, whether they vary among different subgroups of the population. We show that women and individuals with lower preretirement income have stronger negative effects of early retirement. On the contrary, individuals from more affluent socioeconomic background seem to benefit from early retirement.

The remainder of this article is organized as follows. In the second section, we briefly review the context in which the substantial question is set and the literature on retirement effects on health. In the third section, we present the linked data set we built, also through some descriptive analyses. In the fourth section, we introduce our methodological approach, formalizing assumptions, and defining parameters of interest using the potential outcome framework. We then propose different matching designs including a novel one based on health trajectories. In the fifth section, we present and discuss empirical results obtained. The sixth section concludes the article.

## The Timing of Retirement and Health: Theory and Empirical Evidence

Population aging is identified with the increase in old-age dependency ratios, that is, the ratio of population in ages traditionally associated with retirement over population in ages traditionally associated with employment. Old-age dependency ratios have been increasing in advanced societies, and pension reforms aimed at increasing the age at retirement have been seen as “natural” policy responses to these increases, associated with increasing longevity and decreasing fertility (Vaupel 2006). Pension reforms have included structural modifications of retirement systems, changes to disability and employment insurance programs, and the promotion of active labor–market policies aimed at older workers, such as gradual retirement and more individualized pension plans (Cooke 2006). The actual range of retirement ages has therefore expanded, making the transition to retirement “longer and fuzzier” (Han and Moen 1999; Kohli and Rein 1991). Moreover, intermediate states between labor force exit and the receipt of pensions have emerged as a consequence of phenomena like labor force reentry (Reimers and Honig 1993; Skoog and Ciecka 2010), bridge employment (Ruhm 1990), and partial retirement. Retirement has therefore become more “destandardized”, “desinstitutionalized,” and “individualized” (Guillemard and Rein 1993; Kohli 1991).

What are the consequences of this postponement and destandardization of retirement? A topic of major concern is the effect of the timing of retirement on individual health and well-being. For instance, the negative effects of changes in retirement patterns could cumulate at the aggregate level and counterbalance, with additional health-care costs, the positive effects of postponing the exit from the labor force. Several studies have shown that retirement at younger ages is associated with adverse effects on health (Burdorf 2010; Hult et al. 2010; Westerlund et al. 2010). Moreover, the heterogeneity of retirement patterns may have important implications on inequality among elderly people (Fasang 2012). However, selection into retirement due to previous individual health trajectories is a confounder in the study of the health consequences of retirement and its timing, as it is safe to assume that individual decisions to retire are also affected by health reasons. That is, those who retire early tend to have worse health conditions and prospects with respect to those who retire later. In addition to health conditions and prospects, the decision to retire is influenced by other individual characteristics (e.g., education, income, and marital status), preretirement work trajectories (e.g., work and unemployment spells), and other life-course events (e.g., the retirement status of the partner). All these factors are also likely to affect postretirement health outcomes.

According to the literature, retirement, and its timing, may affect health on several pathways. These pathways might push effects toward opposite directions. Moreover, the effects of retirement might differ according to individual characteristics. In what follows, we briefly review the pathways discussed in the literature and the available empirical evidence.

Retirement might trigger *positive* health effects, including a positive effect of early retirement. For instance, retirees are no longer exposed to the physical fatigue of their occupation. At the same time, retirement may have beneficial effects on stress and mental health. However, as the effect of work-related stress accumulates over time and might have long-term repercussions (Halfon and Hochstein 2002; Johnson and Hall 1988), ending the exposure to work-related stress may not be sufficient to reverse its long-term negative effects.

On the contrary, retirement might trigger *negative* health effects, with additional benefits for the postponement of early retirement. For instance, retirement itself might exert stress and cause a decrease in the well-being of individuals who strongly identify themselves with their job (Akerlof and Kranton 2000). Retirement may also be associated with lower ambitions and the loss of a societal role for elderly people (Crawford 1972; Havighurst 1954). Retirees tend to reduce their social ties, receiving less potential support from their colleagues, and several studies have highlighted the importance of social ties for health and mortality (Ellwardt et al. 2015; Holt-Lunstad, Smith, and Layton 2010). Moreover, according to the economic model of Grossman (1972), retirement reduces incentives to invest in health, as health is no longer a necessary factor in productivity. In this economic approach, health is seen as an investment good that raises productivity, but it is also a source of direct utility. If, on the one hand, this is consistent with a deterioration of health after retirement, on the other hand, the elderly may still invest in health independently from its job-related implications. Upon retirement, the value of time is reduced, so the time cost of, for instance, engaging in physical activity or visiting the physician drops. Retirees have more leisure time that can be spent to improve their physical activity (Insler 2014). Eibich (2015), for example, found that retirees are more likely to quit smoking and exercise more. The reverse can be true as well, the freed-up time may also be used on unhealthy activities like excessive calorie intake or alcohol consumption (Sjösten et al. 2012; Zins et al. 2011).

The effects of retirement may also be *heterogeneous* and modified by individual characteristics and life-course trajectories. For instance, those who were employed in physically demanding or stressful occupations would specially benefit from the relief associated with retirement (Mazzonna and Peracchi 2014).

What does the available empirical evidence show? It is safe to say that findings are mixed. Analyses based on cross-sectional data usually find that those who retire earlier have on average worse postretirement health as compared to those who retire later. Longitudinal studies looking at changes in health before and after retirement show inconclusive results. Although these studies tend to suggest a *positive* effect of retirement on self-reported measures of health, there are several reasons for which these results should be taken with caution. First and foremost, most of these studies focus on retirement at any age and not on the differential effect of age at retirement. Early "voluntary" retirement may have a different effect on health as compared to standardized compulsory retirement. Second, many studies that look at health before and after retirement do not make use of a "control group" and do not compare the outcomes for retirees with those of workers who are still in the labor force. Several articles using longitudinal data from a large cohort of workers of the French GAZEL company (Goldberg et al. 2007; Vahtera et al. 2009; Westerlund et al. 2009) show positive effects based on self-reported health measures on mental and physical fatigue, depressive symptoms, and a decrease in sleep disturbances. However, a strong limitation of these studies is that analyses only focus on retirees, ignoring eventual changes over time in the same health outcomes among people who keep on working. Third, "anticipation effects" may be observable before retirement. Retirement is a planned life-course transition, and it depends on many factors. Individuals who expect to retire soon may adjust their behavior before retiring. If these adjustments, in turn, affect postretirement health outcomes, it is impossible to capture the effect of retirement by only looking at changes in health status. Indeed, descriptive results from different countries show that the improvement in health starts before the actual age at retirement (Westerlund et al. 2009). Fourth, long-term effects may differ from short-term ones, and long-term effects are subject to selection because of mortality. Although several studies show an immediate beneficial effect of retirement on self-reported health, the long-term effects on objective health measures and mortality are more controversial. Westerlund et al. (2010) could not, for instance, find a positive effect of retirement when looking at respiratory diseases, diabetes, coronary heart disease, or stroke.

The results we discussed are likely to be importantly affected by selectivity, since in an environment in which it is possible to choose, the individual decision to retire is influenced by health. Moreover, other preretirement factors such as socioeconomic status, marital status, occupation, and work trajectories before retirement may act as confounders in the association between the timing of retirement and subsequent health. Some studies have explicitly built designs through which it might be possible to obtain estimates of the "causal" effect of retirement on health, and their results tend to be contrasting. The main strategy of these studies is to use exogenous variation in retirement policies as an instrumental variable in order to estimate the effect of retirement on later health outcomes. For instance, Kuhn, Wuellrich, and Zweimüller (2010) exploit changes in unemployment rules that allowed workers to retire early in some regions in Austria. Their results show *negative* causal effects on health (measured as mortality before the age of 67) of early retirement for men. Analogously, using the English Longitudinal Study of Ageing, Behncke (2012) found that retirement significantly increases the risk of being diagnosed with a chronic condition. Similarly, Mazzonna and Peracchi (2012) found evidence that retirement increases the age-related decline of health and cognitive abilities for most workers. On the contrary, a number of studies find that retirement has a positive impact on health (Blake and Garrouste 2013; Charles 2002; Coe and Lindeboom 2008; Coe and Zamarro 2011; Hallberg, Johansson, and Josephson 2014; Insler 2014; Mein et al. 2003; Neuman 2008). Finally, other studies show no evidence of effects of early retirement on health (Hult et al. 2010; Lindeboom and Andersen 2010).

Some empirical evidence explicitly points to *heterogeneous* effects. Using data from the Survey of Health Ageing and Retirement in Europe, Mazzonna and Peracchi (2017) found evidence of a positive immediate effect age-related decline of health and cognitive abilities of retirement for those employed in highly physically demanding jobs.

## Data and Descriptive Analyses

### Context and Data

The entire pension system in Sweden has been reformed in 1998. With the reform, Sweden replaced its former pay-as-you-go-defined benefit system with a pay-as-you-go notional-defined contribution system, and an advance funded second pillar with privately managed individual accounts, supplemented with a guarantee at age 65 for persons with low lifetime earnings. The new pension legislation was implemented specifying a gradual transition from a public defined benefit plan to a defined contribution plan. While the reformed pension system went into effect in 1999, during the transition period, benefits were drawn from both the old and the new systems. The old system combined a flat rate universal benefit (*Folkpension*) with an earnings-related supplement. A full earnings-related benefit could be obtained with 30 years of covered earnings at age 65 based on an average of the best 15 years. The system offered the options of claiming full retirement benefits at age 65, claiming reduced benefits from age 60, or claiming actuarially increased benefits if receipt was delayed past age 65. In addition, since 1976, the Swedish national pension system has had a unique program that allows qualified workers aged 60–64 to draw partial pensions if they reduce their working hours to within prescribed limits (Packard 1982).

Within the new system, retirement age is flexible, and benefits can be withdrawn from age 61. Upon retirement, annual benefits are calculated by dividing the balance in the notional account by an annuity divisor linked to life expectancy. Early retirees who choose to retire before age 65 have reduced pension benefits, while those who delay their retirement after age 65 receive higher pensions. Besides earnings-related benefits, the pension system also guarantees a minimum pension payable from age 65, financed from general tax revenues. The transitional rules cover a long period. Those born in 1937 or earlier receive their pension under the old system. Those born in 1954 or later will be paid entirely from the new system. Persons born between 1938 and 1953 will receive pension payments from both systems; the share of the pension that is derived from the old system will be largest for persons born in 1938 and smallest for those born in 1953 (Selén and Ståhlberg 2007).

In our analyses, we will use data from the Linnaeus Database, a longitudinal record linkage data set developed at the Centre for Demographic and Ageing Research at Umeå University. The Linnaeus Database was created in order to facilitate studies concerning the relationship between socioeconomic conditions and health from an aging perspective. The database links nationwide longitudinal data from various registers from Statistics Sweden and the National Board for Health and Welfare. Thus, yearly data, for example, on hospitalization and socioeconomic conditions, are available on an individual level from 1990 to 2006 for the whole Swedish population (for a detailed description of the Linnaeus Database, see Malmberg, Nilsson, and Weinehall 2010).

More specifically, we use data regarding *all* individuals born 1935–1946, and we select on those born in Sweden and who lived in Sweden in 1990. The follow-up period for our observation is 1990–2006. Hence, we can follow individuals from the age of 55–71, a period in life when most individuals in Sweden withdraw from the labor force. Besides information on basic sociodemographic characteristics, we can access yearly information on the individual's income from salary or own enterprise, unemployment benefits, occupational pensions, old-age pensions and early retirement pensions related to sickness or disability, the highest education level, and marital status (from Statistics Sweden). From the Inpatient Register, we also have information on days spent in hospital and on the year of death (if observed).

**Table 1.** Age at Retirement by Gender.

| Retirement Age | Men (*n*) | Cumulative, Percent | Women (*n*) | Cumulative, Percent |
|---|---|---|---|---|
| Before 60 | 57,725 | 10.42 | 42,162 | 7.71 |
| 60 | 16,075 | 13.33 | 11,389 | 9.79 |
| 61 | 28,457 | 18.47 | 21,043 | 13.64 |
| 62 | 21,607 | 22.37 | 19,453 | 17.19 |
| 63 | 21,815 | 26.31 | 21,402 | 21.11 |
| 64 | 21,253 | 30.14 | 27,665 | 26.16 |
| 65 | 98,975 | 48.02 | 115,290 | 47.24 |

There is a linkage to the individual's partner for those having one, and therefore similar information on partners is available.

Since the interest of this study is to look at the effect of the age at retirement on health outcomes, the definition of the timing of retirement is essential. Note that register data have been created for taxation purposes and do not have information on exact date of retirement but only on the yearly composition of income. We define the year of retirement as the first year in which the annual income from pension exceeds the annual labor earnings. In annual labor earnings, we also include transfers connected to unemployment and labor market measures. These transfers are not given to individuals after the age of 65. This definition of retirement is concordant with Stenberg, de Luna, and Westerlund (2012). Even though the transition to retirement has become blurred, and the actual range of retirement ages has expanded, making the transition "longer and fuzzier" (Han and Moen 1999; Kohli and Rein 1991), for the sake of simplicity, we define retirement as an absorbing state, so that an individual, once retired, is assumed to be retired for good. Doing so, we restrict our analysis to nonrecurrent events, although there are no limitations to expand the method to recurrent events.

Table 1 displays descriptive statistics on retirement age as defined above. Most men and women in Sweden retire at age 65. However, around 30 percent of men and women retire before age 65 (which we classify as early retirement). Trends in age at retirement are shown in Table 2. As expected, we see a reduction in the proportion of early retirees for later birth cohorts as a results of reforms aimed at postponing retirement age.

### *Health Trajectories Before and After Retirement*

For each individual in our data set, we observe the annual number of days spent in a hospital (hospitalization is recorded in the Inpatient Register as

**Table 2.** Distribution of the Age at Retirement by Birth Cohort (Percent) and Total Sample Sizes (*n*).

| Birth Year | Before 60 | 60 | 61 | 62 | 63 | 64 | 65 | *n* |
|---|---|---|---|---|---|---|---|---|
| 1935 | 9.77 | 3.80 | 6.22 | 5.15 | 6.59 | 9.36 | 40.99 | 71,418 |
| 1936 | 10.03 | 4.09 | 6.49 | 5.16 | 5.83 | 9.21 | 39.21 | 74,353 |
| 1937 | 10.33 | 3.96 | 6.67 | 4.35 | 6.25 | 9.46 | 37.57 | 75,726 |
| 1938 | 10.92 | 3.03 | 5.85 | 6.11 | 5.15 | 6.14 | 39.94 | 79,242 |
| 1939 | 10.80 | 2.58 | 6.48 | 3.87 | 4.98 | 8.88 | 37.97 | 82,234 |
| 1940 | 10.12 | 2.19 | 3.85 | 4.19 | 7.02 | 5.69 | 40.21 | 81,303 |
| 1941 | 10.04 | 2.35 | 3.86 | 5.30 | 5.38 | 6.26 | 37.46 | 84,927 |
| 1942 | 9.35 | 2.27 | 4.39 | 4.67 | 5.39 | 6.23 | — | 98,213 |
| 1943 | 8.76 | 2.21 | 4.35 | 4.27 | 5.30 | — | — | 107,386 |
| 1944 | 8.16 | 1.96 | 4.26 | 4.48 | — | — | — | 115,002 |
| 1945 | 7.18 | 1.64 | 4.23 | — | — | — | — | 116,045 |
| 1946 | 6.12 | 1.44 | — | — | — | — | — | 114,930 |

soon as one night is spent at a hospital in Sweden). Figures 1 and 2 display the average number of days in hospital before and after retirement for men and women retiring at different ages before 65 years of age. The figures show that trends in hospitalization differ substantially between those retiring at a given age and those retiring later on. Individuals tend to have an increase in hospitalization around retirement age. This increase in hospitalization starts around one to two years before retirement and decreases after retirement. This trend is consistent with studies conducted for other countries (Westerlund et al. 2009). On the other hand, the control group, composed by individuals who are not yet retired, shows a gradual linear trend in hospitalization rates.

The fact that the two groups exhibit different trends in health outcomes makes a direct comparison challenging. Retirees are likely to experience negative health shocks before retirement. Therefore, a comparison strategy that does not control for different health trajectories before retirement is bounded to introduce bias in the estimation of the causal effects of retirement.

The data also show if an individual received sick leave benefits while at work (i.e., before retirement) or disability benefits (if sick leave is longer than two weeks) in a given year. These benefits represent proxy measures of health that, in addition to hospitalization, give a more detailed indication of the general health status of an individual. Hospitalization, sick benefits, and disability can thus be combined to define observable health trajectories before retirement.

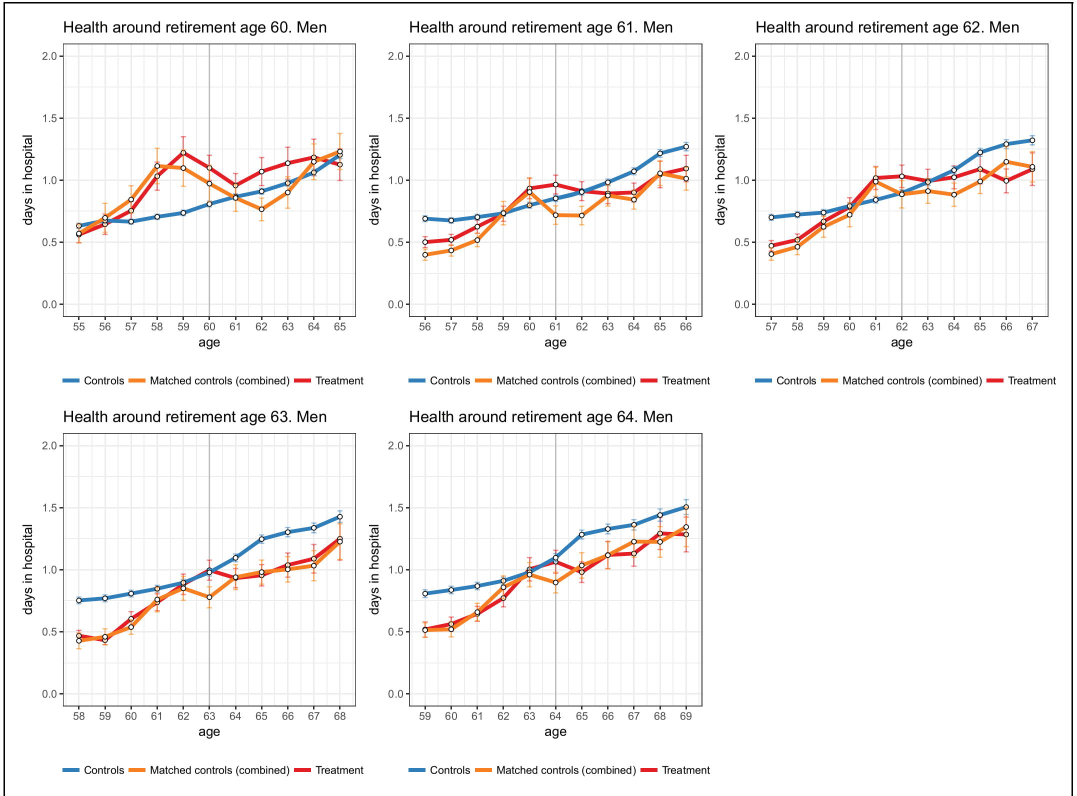


**Figure 1.** Average number of hospitalization days before and after retirement age for men retiring at age 60–64. "Treatment" group refers to those retiring at a given age (marked with a vertical line), the "controls" are those retiring later.

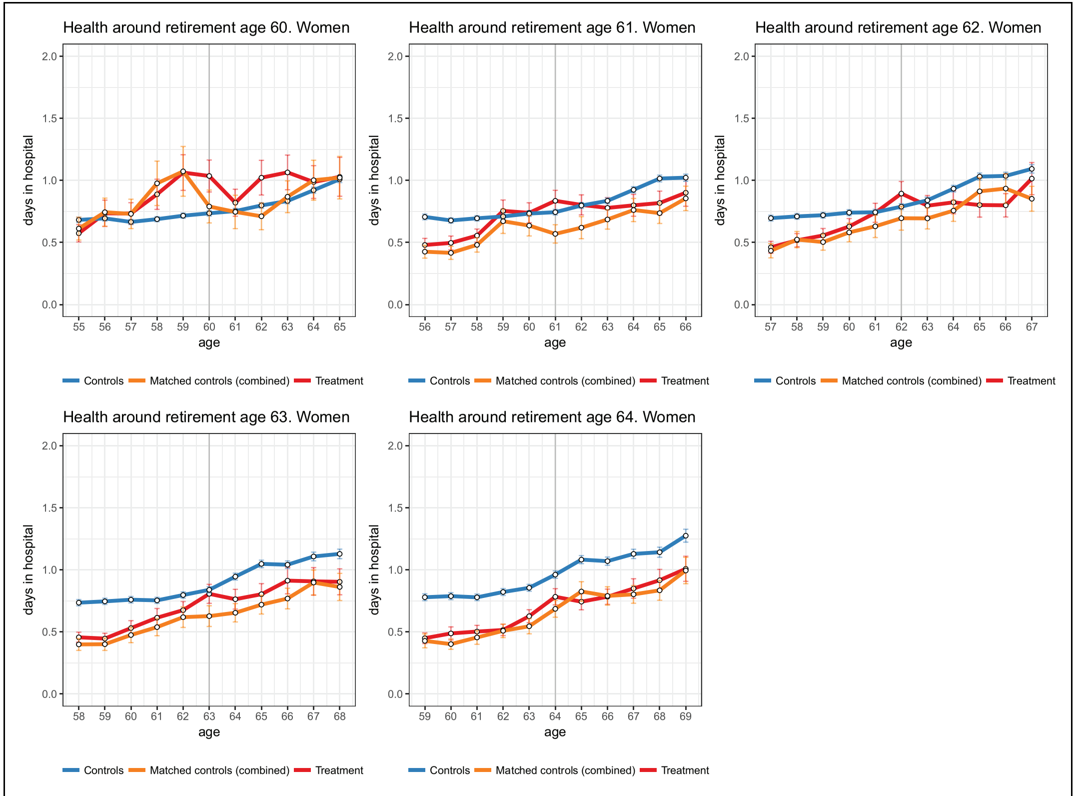


**Figure 2.** Average number of hospitalization days before and after retirement age for women retiring at age 60–64. "Treatment" group refers to those retiring at a given age (marked with a vertical line), the "controls" are those retiring later.

Following a standard approach in sequence analysis, health trajectories can be analyzed by representing the original data, that is, each individual's life course, as a sequence of states. Each individual $i$ can be associated to a variable $s_{it}$ indicating her or his life-course status at time $t$. Assuming that $s_{it}$ takes a finite number of values, trajectories can be represented as strings or sequences of characters, with each character denoting one particular state. The state space (i.e., the alphabet from which sequences are constructed) has a finite number of elements and represents all the possible states that an individual can take in each time period. For instance, a woman who is healthy (in state H) for five years since the start of our follow-up period (e.g., age 55), then is hospitalized and on sick benefits (C) during three years, and then only on sick benefits (S) for the following three years can be described as follows:

HHHHHCCCSSS

In this case, the state space has four values (S for "sick benefits," D for "one day or more at hospital," C for "both sick benefits and one day or more at hospital," and H for healthy meaning here "no sick benefits and zero days at hospital").

In subsequent analyses, we extend the description of life-course trajectories to eight possible states, where we use hospitalization, sickness, and disability benefits. For the individual $i$, the possible states at any year $t$ antecedent retirement are thus

1. No hospitalization and no benefits received in year $t$;
2. No hospitalization, but individual $i$ received sick benefits in year $t$;
3. No hospitalization, but individual $i$ received invalidity benefits in year $t$;
4. No hospitalization, but individual $i$ received both sick benefit and invalidity benefits in year $t$;
5. Individual $i$ spent one day in hospital during year $t$;
6. Individual $i$ spent two days in hospital during year $t$;
7. Individual $i$ spent three days in hospital during year $t$;
8. Individual $i$ spent more than three days in hospital during year $t$.

## Methodological Approach

### *Framework*

A widely used approach to causal reasoning is the potential outcome framework, originally by Neyman (1934; see also Rubin 1990) and developed for observational studies by Rubin (1973). Let us define the timing of a life-course event as a binary treatment variable $T$ ($T = 1$, if an individual retires at age $a$, and $T = 0$, if an individual retires at age $a*$, with $a* > a$). Only individuals who have not retired prior to age $a$ are exposed to the risk of retiring, similarly to what happens in discrete-time event history models. Consider a later outcome of interest (in our study a measure of health). Two potential outcomes are then defined for each unit in the study: the outcome under treatment (the individual retires at age $a$), $Y(0)$, and the outcome under no treatment (the individual does not retire before or at age $a$), $Y(1)$. The difference $Y(1) - Y(0)$ can be interpreted as the *causal effect* of the treatment $T$ at the unit level. This effect is not identified since for each unit either $Y(0)$ or $Y(1)$ is unobserved. It is however well known that, under certain conditions, population-level parameters may be identified. In this article, we focus on the average causal effect of early retirement for those actually retiring early, that is, $\tau = E(Y(1) - Y(0)|T = 1)$, for a given value $a < 65$, since 65 years is the typical retirement age in Sweden. This parameter known as the *average treatment effect on the treated* gives a counterfactual answer on what would have been the average health of those retiring at age $a$, would they have retired later.

The parameter $\tau$ is identified under the following conditions. First no interference are allowed, that is, the potential outcomes of any unit in the study are not affected by the retirement decision of other units. This condition, called the *stable unit value assumption* (e.g., Rubin 1991), seems reasonable in our case at least for individuals who are not partnered. We therefore conduct separate analysis for women and men. Also, for identification purposes, we need to have access to a set of background information $\mathbf{X}$, which is not affected by the treatment $T$, and such that $(Y(0), Y(1), T, \mathbf{X})$ has a joint distribution for which $Y(0), Y(1) \perp\!\!\!\perp T|\mathbf{X}$ and $0 < \Pr(T = 0|\mathbf{X}) < 1$, where "$A \perp\!\!\!\perp B|C$" stands for "A is independent of B given C." This condition is called strong ignorability of the treatment, and it requires that all background information $\mathbf{X}$ affecting both $Y(0)$ and $T$ is observed. Under these two assumptions, we can design a study to estimate the causal effect of the timing of retirement by conditioning on the necessary background information $\mathbf{X}$ in order to obtain an estimator of the causal effect $\tau$.

The strong ignorability assumption is a strong condition and conclusion of observational studies must be interpreted with care. On the one hand, life-course studies often have the opportunity to access rich background information. In our case, this include socioeconomic and health registers and course trajectories. The strong ignorability assumption therefore becomes realistic. On the other hand, conditioning for a large and complex information set needs careful design (de Luna, Waernbaum, and Richardson 2011).

We make use of a *balancing score* $b(\mathbf{X})$, a function of the information set $\mathbf{X}$, such that $T \perp\!\!\!\perp \mathbf{X}|\mathbf{b}(\mathbf{X})$. A cornerstone result in causal inference (Rosenbaum and Rubin 1983) is that if strong ignorability holds, then $Y(0), Y(1) \perp\!\!\!\perp T|b(\mathbf{X})$. This is useful when $b(\mathbf{X})$ is of lower dimension than $\mathbf{X}$, since one may design the analysis by conditioning on the balancing score instead of the original set $\mathbf{X}$. In this respect, balancing scores play an important role in the design of observational studies. Indeed, Rosenbaum and Rubin showed that there exists a one-dimensional balancing score, the scalar $e(\mathbf{X}) = \Pr(T = 1|\mathbf{X})$ called the propensity score. The latter is typically unknown, although in applications it may be modeled and fitted to the data as exemplified below.

## Matching Design

Assume that we have a random sample of $N$ units indexed by $i$, of which $N_1$ units, $i = 1, \ldots, N_1$, are treated (have retired early at age $a$), and $N_0$ units, $i = N_1 + 1, \ldots, N_1 + N_0$, are controls (have not yet retired at age $a$), that is, $N = N_0 + N_1$. We observe $\mathbf{X}_i, T_i$ and the outcome $Y_i = T_i\ Yi(1) + (1 - T_i)Y_i(0)$ for all units.

Given a balancing score $b(\mathbf{X}_i)$, a study targeting $\tau$ may be designed by matching treated with controls having same value for $b(\mathbf{X}_i)$, that is, for each treated unit $i = 1, \ldots, N_1$, picking (herein with replacement) a control unit $j$ such that $b(\mathbf{X}_j) = b(\mathbf{X}_i)$. Denoted by $j(i)$, the index $j$ of the control unit thus chosen as a match for the treated unit $i$. When such exact matching is not possible, for instance, if the balancing score is continuous valued, then a distance measure $\mathcal{D}_b$ in $b(\mathbf{X}_i)$ is used to select the closest match (nearest neighbor matching; Abadie and Imbens 2006) instead of an exact match. Let $\hat{\tau} = 1/N_1 \sum_{i=1}^{N_1}(Y_i - Y_{j(i)})$, then under the strong ignorability assumption $\hat{\tau}$ is a consistent estimator of $\tau$. Inference can be performed using the asymptotic normal approximation together with the standard error of the mean $\hat{\tau}$ (Rubin 1991).

We propose and implement three different matching designs, two of which uses the health trajectories defined earlier.

*Balancing health trajectories through OM.* Let $\mathbf{S}_i = \{S_{i1}, S_{i2}, \ldots, S_{iL}\}$ be the health trajectory of length $L$ for individual $i$, where here $S_{ij}$, $j = 1, \ldots, L$ take one of the height state values defined in Health Trajectories Before and After Retirement subsection. The first design we propose is obtained by matching on health trajectories $\mathbf{S}_i$ using sequence analysis, a family of algorithms used to quantify distances between categorical time series. In particular, OM is a commonly used family of dissimilarity measures derived from the measure originally proposed in the field of information theory and computer science by Levenshtein (1965) and later adapted to the social sciences (Abbott 1995; Kruskal 1983; Lesnard 2006). Basically, OM expresses distances between sequences in terms of the minimal amount of effort, measured in terms of edit operations, that are required to change two sequences, so that they become identical. A set that is composed of three basic operations on sequences is used: $\Omega = \{\iota, \delta, \sigma\}$, where $\iota$ denotes *insertion* (one state is inserted into the sequence), $\delta$ denotes *deletion* (one state is deleted from the sequence), and $\sigma$ denotes *substitution* (one state is replaced by another state into the sequence). To each of these elementary operations $\omega_k \in \Omega$, a specific cost can be assigned using a cost function $c(\omega) : \Omega \rightarrow \mathcal{R}^+$. If $\boldsymbol{K}$ operations must be performed to transform one observed sequence $\mathbf{s}_1$ into another $\mathbf{s}_2$ such that

$$\mathbf{s}_2 = \omega_1 \circ \omega_2 \circ \cdots \circ \omega_K(\mathbf{s}_1) = \omega_.(\mathbf{s}_1),$$

then the transformation cost is defined as $\sum_{j=1}^{K} c(\omega_j)$. The distance between two sequences can thus be defined as the minimum cost of transforming one sequence into the other one:

$$\mathcal{D}_s(\mathbf{s}_1, \mathbf{s}_2) = \min_\omega \left\{ \sum_{j=1}^{K} c(\omega_j) \text{ s.t. } \mathbf{s}_2 = \omega_.(\mathbf{s}_1) \right\}.$$

Sequence analysis and OM are often used in conjunction with cluster analysis to identify patterns in the data and highlight typical life-course trajectories (Abbott and Tsay 2000; Aisenbrey and Fasang 2010b; Barban 2013; Barban and Billari 2012). In this article, we propose to use the OM distance measure to match treated individuals with controls as described above. Substitution costs are set to be inversely proportional to transition frequencies between two states (Piccarreta and Billari 2007). More specifically, we propose to match individuals who have the most similar health trajectories before retirement. To our knowledge, this is the first attempt to use the rich information obtained from sequence analysis for the design of an observational study.

*Propensity score matching.* Propensity score matching is a commonly used design in observational studies due to its balancing property. Departing from a covariate vector $\mathbf{W}_i$, the propensity score $e(\mathbf{W}_i)$ is typically parameterized using a linear logistic regression model $e(\mathbf{W}_i;\gamma) = \frac{\exp(\gamma'\mathbf{W}_i)}{1+\exp(\gamma'\mathbf{W}_i)}$; see Waernbaum (2010) for robustness properties of such an approach. Using maximum likelihood yields fitted values $e(\mathbf{W}_i;\hat{\gamma})$ for all units, which are then used to match treated to controls, using the Euclidean distance in $e(\mathbf{W}_i;\hat{\gamma})$, denoted $\mathcal{D}_e$.

We base our propensity score matching on the following variables, measured before year $t$ corresponding to the year of retirement for the treatment group:

1. Education at time $t-1$ (three categories: low, medium, and high),
2. Cumulative income from time $t-5$ to $t-1$,
3. Marital status at time $t-1$,
4. Partner's retirement status at time $t-1$,
5. Unemployment status at time $t-5, \ldots, t-1$, and
6. hospitalization at time $t-5, \ldots, t-1$ (number of days during a year).

*Combining OM and propensity score matching.* We finally consider a third design where matching is done using a combination of the two approaches. With this design, we aim at balancing the pretreatment information set $\mathbf{X}_i = (\mathbf{S}_i, \mathbf{W}_i)$. These information sets are very different in nature and we have therefore used above different distance measures, $\mathcal{D}_s$ and $\mathcal{D}_e$, to balance separately $\mathbf{S}_i$ and $\mathbf{W}_i$, respectively. Here, we aim at proposing a design balancing both information sets simultaneously, and we need thus to define a new distance measure combining $\mathcal{D}_s$ and $\mathcal{D}_e$. We propose the following combined distance, making sure to standardize the combined distances to avoid one dominating the other. Thus, the distance between two values of $\mathbf{X}_i$, $\mathbf{x}_1$ and $\mathbf{x}_2$, $\mathcal{D}_c(\mathbf{x}_1,\mathbf{x}_2) = \frac{1}{\max_{k,l}\mathcal{D}_e(\mathbf{w}_k,\mathbf{w}_l)}\mathcal{D}_e(\mathbf{w}_1,\mathbf{w}_2) + \frac{1}{\max_{k,l}\mathcal{D}_s(\mathbf{s}_k,\mathbf{s}_l)}\mathcal{D}_s(\mathbf{s}_1,\mathbf{s}_2)$, is used in order to match treated with controls. To avoid issues related to the introduction of specific changes in pension regulation, we match exactly on birth year. Similarly, given the large sample size, we are able to match exactly on educational level. That is, we are able to match individuals who are born in the same year and have the same educational level at the time of retirement.

*Covariate balancing under matching procedures.* Table 3 and Figure 3 show the balancing of covariates before treatment (Imai, King, and Stuart 2008; Stuart 2010). For space limitations, we report the results only for one specific

**Table 3.** Covariate Balancing Under Different Matching Strategies—Men Retiring at Age 61.

| Variable | Treated | Controls | Mean Difference | Matched Controls on Health Trajectories | Mean Difference | Matched Controls on Propensity Score | Mean Difference | Matched Controls on Combined Method | Mean |
|---|---|---|---|---|---|---|---|---|---|
| Hospitalization, $t-5$ | 0.501 | 0.690 | .049 | 0.525 | .006 | 0.425 | .020 | 0.399 | .027 |
| Hospitalization, $t-4$ | 0.520 | 0.676 | .041 | 0.501 | .005 | 0.445 | .020 | 0.434 | .023 |
| Hospitalization, $t-3$ | 0.626 | 0.703 | .017 | 0.635 | .002 | 0.537 | .020 | 0.518 | .024 |
| Hospitalization, $t-2$ | 0.730 | 0.733 | .001 | 0.662 | .013 | 0.677 | .010 | 0.735 | .001 |
| Hospitalization, $t-1$ | 0.934 | 0.798 | .019 | 0.788 | .020 | 0.959 | .004 | 0.905 | .004 |
| Unemployment, $t-5$ | 0.045 | 0.094 | .049 | 0.095 | .050 | 0.040 | .005 | 0.039 | .006 |
| Unemployment, $t-4$ | 0.050 | 0.104 | .055 | 0.109 | .059 | 0.048 | .002 | 0.046 | .003 |
| Unemployment, $t-3$ | 0.065 | 0.111 | .046 | 0.117 | .053 | 0.067 | .002 | 0.066 | .001 |
| Unemployment, $t-2$ | 0.097 | 0.115 | .019 | 0.124 | .028 | 0.115 | .018 | 0.112 | .016 |
| Unemployment, $t-1$ | 0.057 | 0.119 | .062 | 0.126 | .069 | 0.065 | .008 | 0.067 | .010 |
| Low education | 0.298 | 0.447 | .149 | 0.434 | .136 | 0.315 | .017 | 0.321 | .022 |
| Medium education | 0.427 | 0.365 | .062 | 0.369 | .058 | 0.413 | .014 | 0.416 | .011 |
| High education | 0.272 | 0.182 | .090 | 0.194 | .078 | 0.269 | .003 | 0.262 | .010 |
| Married | 0.715 | 0.700 | .034 | 0.727 | .026 | 0.732 | .038 | 0.740 | .054 |
| Partner retired | 0.061 | 0.042 | .019 | 0.041 | .020 | 0.063 | .002 | 0.066 | .005 |
| Income (5 years before) | 2,597 | 2,414 | .077 | 2,513 | .035 | 2,378 | .092 | 2,385 | .089 |

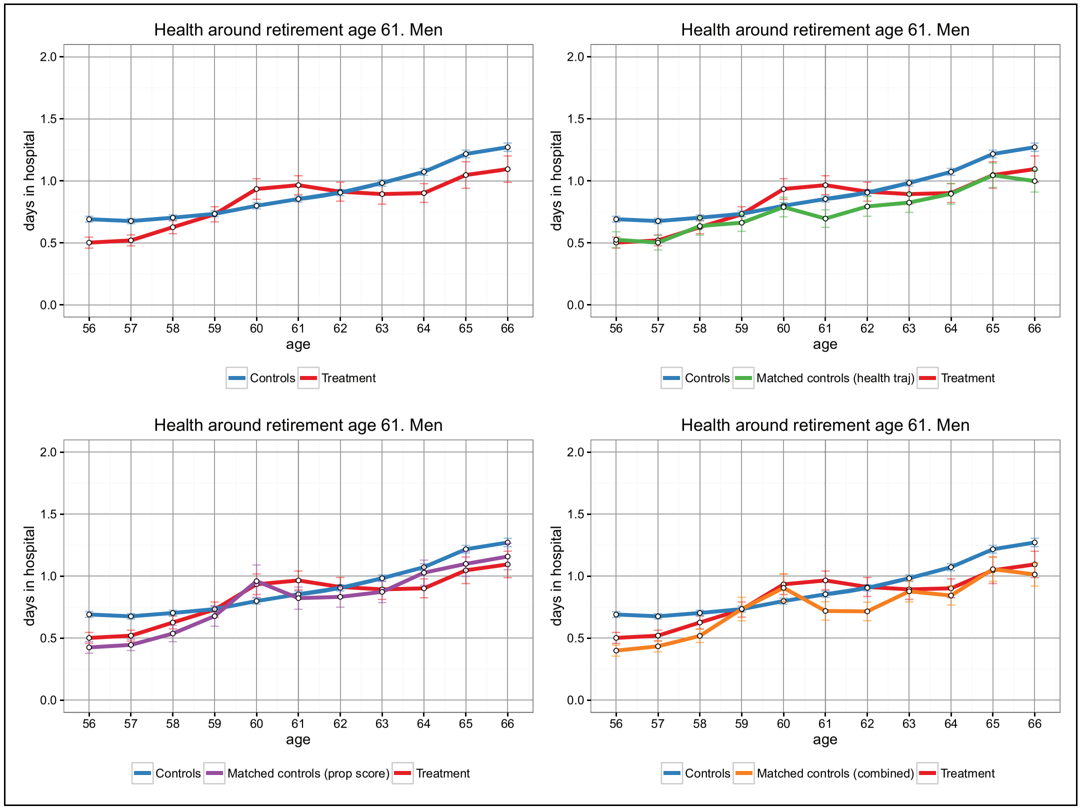


**Figure 3.** Average number of hospitalization days before and after retirement for men retiring at age 61. Treatment group (red line) refers to those retiring at age 61, control group (blue line) refers to those retiring after age 61, and matched controls (green, purple, and orange lines) refer to matched individuals under different matching strategies.

treatment (men, retirement at age 61). Other descriptive results of covariate balance are available in the Online Supplementary Material. Results show that all the three matching strategies are able to improve on the balancing of hospitalization trajectories before retirement, since the trend of hospitalization before retirement of the matched controls follows the one of the treated (Figure 3). Finally, in Table 3, we display the balancing properties of the variables used in the propensity score estimation. We see that balancing properties varies with the different matching strategies.

## Results

We analyze two types of health outcomes: First, the average number of days in hospital for the first five years after retirement as a continuous measure. Second, we examine mortality, conditional on survival to retirement age. We model mortality using a semiparametric proportional hazard model (Cox regression model), estimating the relative risk ratio (RRR) for those who retire at age $a$, compared to those who retire at age $a^* > a$. The combination of a morbidity and a mortality measure allows us to assess the effect of retirement age in a comprehensive way since morbidity is censored by death (Blossfeld and Rohwer 2002). Furthermore, we examine the possible heterogeneity of treatment effects by focusing on mortality only. The matching procedure is based on OM distances calculated using the R package TraMineR (Version 2.0-7) (Gabadinho et al. 2011), while Cox regression models are estimated using the R package survival (Therneau 2015).

### *Age at Retirement and Subsequent Hospitalization*

We compare the hospitalization of retirees at age $a = 60, \ldots, 64$ and their respective matched controls as defined in the previous sections. Tables 4 and 5 report the average difference in number of days of hospitalization between retirees and matched controls ($\hat{\tau}$), one to five years after retirement. For space limitation, we report only the comparison with the combined matched controls. Results based on other matching strategies are available upon request.

Results indicate that the differences in hospitalization are limited to the first years after retirement and to retirement at early ages. The more the age at retirement approaches age 65, the weaker are the differences in hospitalization. In contrast with descriptive results, retirees are expected to spend at least the same amount of days in hospital as their comparison group. Differences are salient in the first years after retirement and are attenuated with the increase in retirement age. These results indicate a weak, if any, causal effect

**Table 4.** Average Difference in Hospitalization After Retirement—Combined Matching (Men).

| | Retirement at Age 60 | | Retirement at Age 61 | | Retirement at Age 62 | | Retirement at Age 63 | | Retirement at Age 64 | |
|---|---|---|---|---|---|---|---|---|---|---|
| | $\hat{\tau}$ | *p* Value | $\hat{\tau}$ | *p* Value | $\hat{\tau}$ | *p* Value | $\hat{\tau}$ | *p* Value | $\hat{\tau}$ | *p* Value |
| $t+1$ | .10 | .09 | .20 | .00** | .08 | .13 | −.01 | .45 | −.05 | .21 |
| $t+2$ | .30 | .00** | .02 | .39 | .14 | .02* | −.03 | .35 | .00 | .49 |
| $t+3$ | .24 | .01** | .06 | .15 | .10 | .10 | .03 | .32 | −.10 | .12 |
| $t+4$ | .04 | .37 | −.01 | .45 | −.15 | .03* | .06 | .26 | .07 | .23 |
| $t+5$ | −.11 | .14 | .08 | .13 | −.02 | .42 | .02 | .42 | −.06 | .29 |

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

**Table 5.** Average Difference in Hospitalization After Retirement—Combined Matching (Women).

| | Retirement at Age 60 | | Retirement at Age 61 | | Retirement at Age 62 | | Retirement at Age 63 | | Retirement at Age 64 | |
|---|---|---|---|---|---|---|---|---|---|---|
| | $\hat{\tau}$ | *p* Value | $\hat{\tau}$ | *p* Value | $\hat{\tau}$ | *p* Value | $\hat{\tau}$ | *p* Value | $\hat{\tau}$ | *p* Value |
| $t+1$ | .07 | .20 | .18 | .00*** | .10 | .04* | .11 | .02* | −.08 | .06 |
| $t+2$ | .31 | .00*** | .09 | .06 | .07 | .15 | .08 | .07 | −.01 | .45 |
| $t+3$ | .20 | .02* | .04 | .28 | −.11 | .07 | .14 | .02* | .05 | .19 |
| $t+4$ | −.01 | .45 | .08 | .10 | −.14 | .04* | .01 | .45 | .08 | .09 |
| $t+5$ | .01 | .48 | .05 | .27 | .16 | .03* | .04 | .29 | .01 | .43 |

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

of retirement age on subsequent health once selection into the timing of retirement is taken into account (Figures 4 and 5).

## *Age at Retirement and Subsequent Mortality*

Figures 6 and 7 show the nonparametric estimates of the survival curves for the two groups. Retirees have higher risk of death after retirement compared to their control group. With the exception of men who retire at age 64, the survival curves of all other treatment groups differ significantly from their matched controls.[1] To give an example of the magnitude in differential mortality rates, we calculate the difference in probability to survive until age 70, conditional on age at retirement. Both men and women who retire at age 60 have a 2 percent lower survival probability to age 70 compared to those who retire later. Mortality differentials decrease with retirement age.

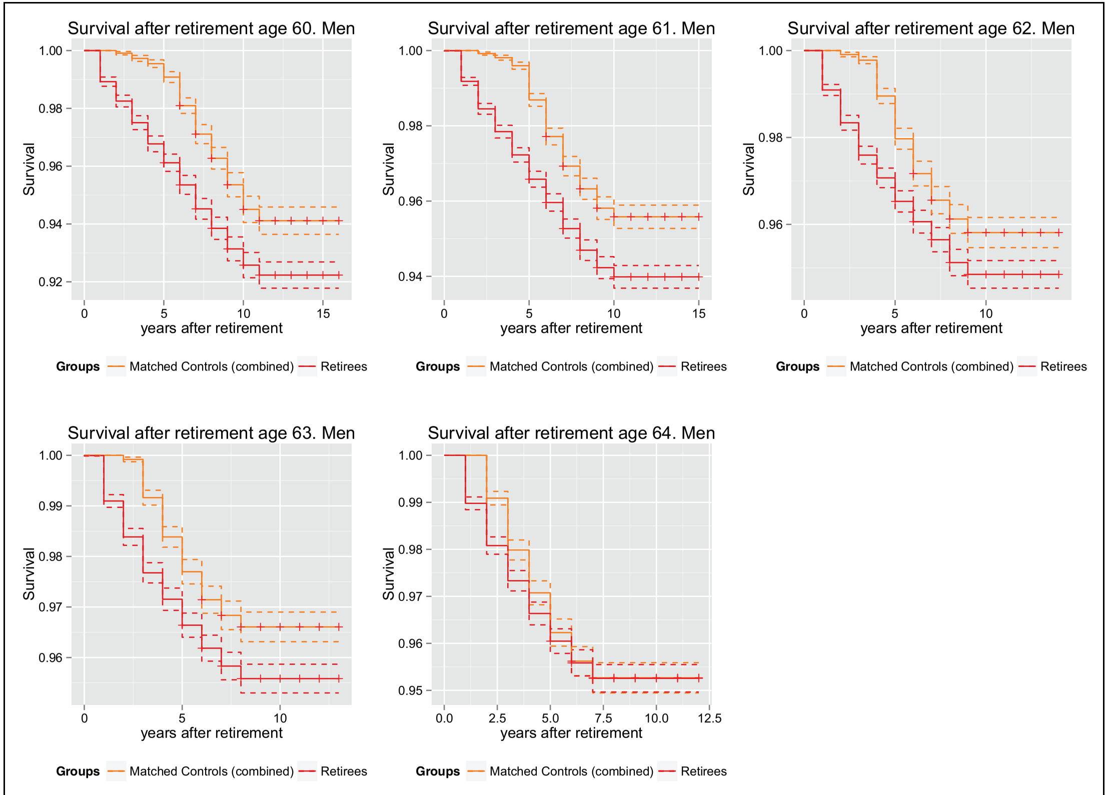


**Figure 4.** Kaplan–Meier survival estimates by age at retirement. The red line indicates the estimated survival probability of retirees, the orange line indicates the survival probability of the matched control group. Dotted lines indicate 95 percent confidence interval. Men retiring at age 60–64.

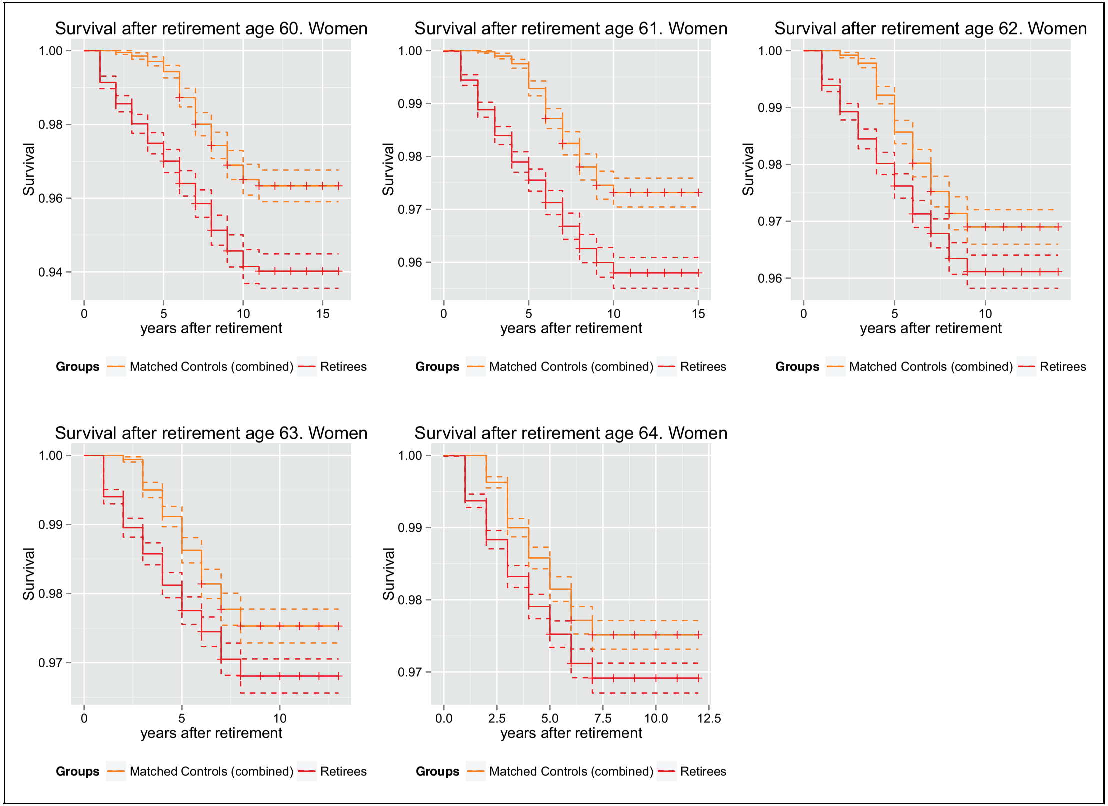


**Figure 5.** Kaplan–Meier survival estimates by age at retirement. The red line indicates the estimated survival probability of retirees, the orange line indicates the survival probability of the matched control group. Dotted lines indicate 95 percent confidence interval. Women retiring at age 60–64.

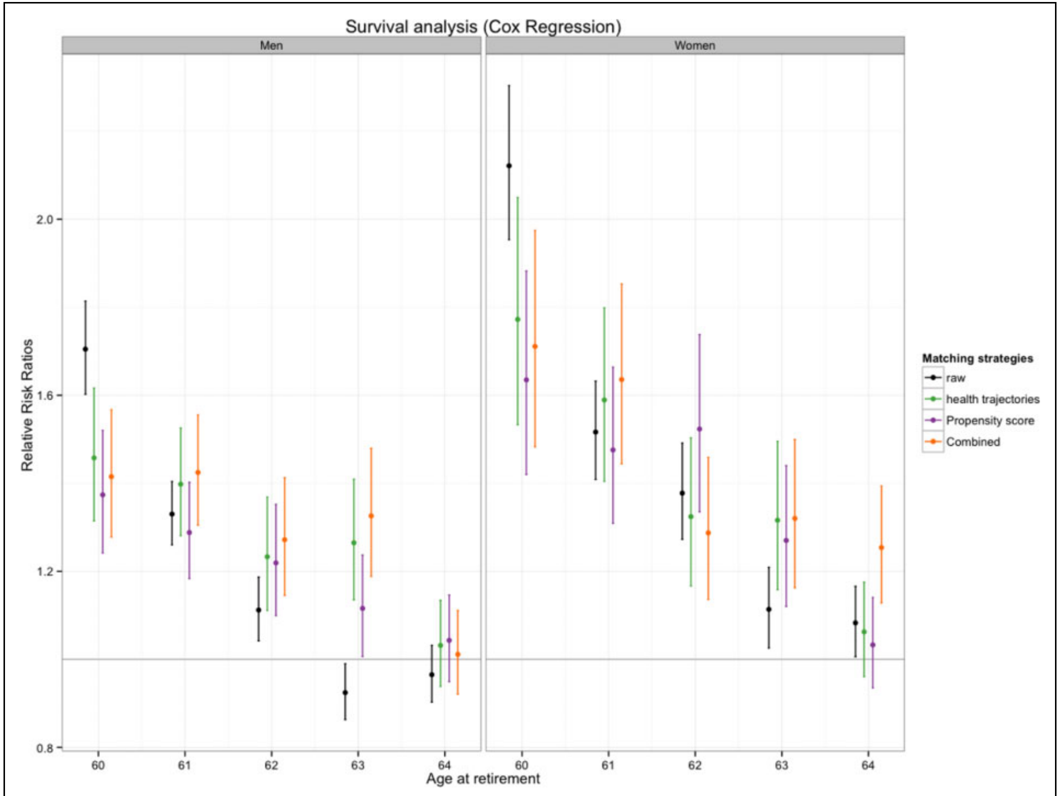


**Figure 6.** Relative risk ratios of death after retirement. Cox regression model estimates with 95 percent confidence intervals.

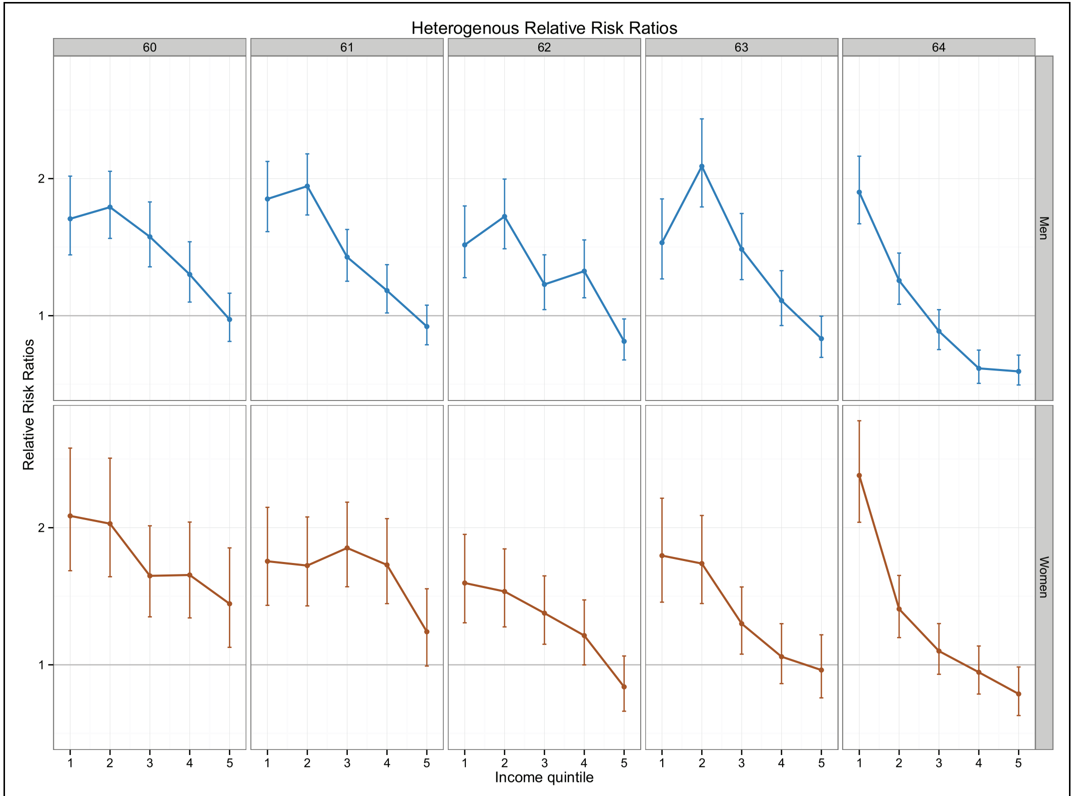


**Figure 7.** Heterogeneous treatment effects. Relative risk ratios of death after retirement by income strata 95 percent confidence intervals.

Men who retire at age 64 have the same survival probability to age 70 than their matched control group. Women who retire at age 64 have 0.6 percent lower survival probability to age 70 compared to their suitable control group.

To summarize the differential survival of retirees and their matched control group, we calculated the RRRs of death by age at retirement. RRRs are calculated using a proportional hazard model (Cox regression), in which we compare the risk of death of retirees at age $a$ with their suitable matched controls. The hazard model is

$$\lambda(t|T_i) = \lambda_0(t)\exp\,(\beta T_i), \tag{1}$$

for any given time $t > a$ and $T_i$ as earlier the indicator of treatment (retirement at age $a$). Under the assumption of proportional hazards, we estimate $\exp(\beta)$ as a measure of RRR. This measure takes into account right censoring and provides an estimate of the differential mortality of the different groups. Figure 6 shows the RRRs. RRR higher than 1 implies higher risk of mortality of retirees compared to the control group. Our results indicate that early retirement is associated with higher mortality. This effect declines with age at retirement and becomes negligible with retirement at age 64. We observe high selection effect only on very early retirement (age 60). Our estimates indicate that, once we include selection in the estimation model, RRR decrease substantially.

## *Heterogeneous Effects*

Although in the previous sections, we show that our matching strategies can achieve a good balancing both on health trajectories and on characteristics at the moment of retirement, this does not exclude that retirement timing may have effects that differ between individuals. For instance, characteristics such as occupation or physical fatigue experienced during their work career may modify the effect of retirement timing on subsequent health. One could hypothesize that individuals who are more subject to physical work may enjoy positive effects from early retirement. On the other hand, individuals who retire early are more subject to forgone earnings and their future pension will be lower. Thus, we analyze if there exists strata-specific effects. More specifically, we estimate the effect differentially for preretirement income. We divide the sample in five quintile classes based on the average income in the five years prior to retirement and fit for each class the hazard model 1.

Figure 7 shows that the effect of retirement on the probability of dying is not constant across income quintiles. Individuals with lower preretirement income suffer the most from early retirement, while individuals with higher preretirement income are not negatively affected. Although these results are not meant to be exhaustive in describing which factors modify the effect of retirement, we show that there exists a heterogeneous health effect of retirement timing. As a consequence, we can expect that the relative change in pension income is less relevant for richer individuals.

## Discussion

We propose a new matching approach to investigate the causal effect of the timing of life-course events on subsequent outcomes. Our approach combines the literature on the analysis of life-course trajectories with the literature on causal inference. We apply our method to the study of age at retirement in Sweden. Early retirees tend to experience worst preretirement health trajectories (hospitalization patterns and trends) with respect to those who retire later. This is particularly relevant in the case of early retirement (before age 65), since the largest differential in health outcomes is observed among individual who anticipate their retirement. To account for selection, we develop a new matching approach that combines information on health trajectories with sociodemographic characteristics fixed in time. We develop this technique as an extension of the nearest neighbor matching estimator adopting the OM metric commonly used in sequence analysis. We then compare the covariate balance under three different matching strategies: matching only on health trajectories, matching on propensity score–based time invariant covariates, and a combined matching approach. All matching strategies produce a good balance of covariates and give consistent results.

Our analysis shows that both time-variant (health trajectories before retirement) and time-invariant (sociodemographic characteristics) confounders need to be taken into account. Although retirees seem to have a faster decline in health after retirement, this effect is masked by different trajectories in health before retirement. Our analysis shows that the health trajectory itself is a source of confounder, since the decision on when to retire is often linked to the antecedent health history. People who experience health shocks are more likely to anticipate retirement. Once these selection issues are taken into account, the negative effect of retirement on hospitalization is reduced substantially. For what concern survival, our analysis shows that early retirement has a negative effect, even after controlling for selection. Early retirement is associated with higher mortality. Men and women who retire at age 60 have a 2 percent decrease in survival probability at age 70 compared to those who retire later. This difference attenuates with increased retirement age. As other matching methods, our approach also allows for heterogeneous treatment effect. We show that the effects of early retirement are highly heterogeneous on preretirement income. Individual with low preretirement income suffer the most from early retirement, while individuals from higher preretirement income tend to benefit from retirement. This may suggest that individuals in higher socioeconomic position are affected less by the relative change in income due to retirement. Our analysis is limited in its scope. We restrict our analysis to hospitalization and mortality and we do not distinguish the effect on different pathologies or cause of death. Moreover, using register data, we could not distinguish between different preretirement occupations.

Similarly to other matching techniques, the approach we propose is based only on observable confounders and does not take into account the effect of unobservable characteristics. For instance, unobservable shocks experienced before retirement associated both with the decision of retirement and subsequent health trajectory may bias our estimates. Nevertheless, the novelty of our approach is to provide a framework that combines information on pre-treatment trajectories, widely used in the literature of life-course analysis, with other techniques used in the literature of causal inference, such as propensity score matching.

## Acknowledgment

We acknowledge the financial support of the Swedish Research Council and the Swedish Research Council for Health, Working Life and Welfare.

## Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

## Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: Financial support was provided by the Swedish Research Council and the Swedish Research Council for Health, Working Life and Welfare. N. Barban received funding from a UK ESRC/NCRM SOCGEN grant (ES/N011856/1) and from the European Research Council via an ERC Consolidator Grant SOCIOGENOME (615603) awarded to M. Mills (see www.sociogenome.com).

## Supplemental Material

Supplementary material for this article is available online (http://nicolabarban.com/RetirementSweden).

## Note

1. Based on log-rank tests, results are available upon request.

## References

Abadie, A. and G. W. Imbens. 2006. "Large Sample Properties of Matching Estimators for Average Treatment Effects." *Econometrica* 74:235-67.

Abbott, A. 1995. "Sequence Analysis: New Methods for Old Ideas." *Annual Review of Sociology* 21:93-113.

Abbott, A. and A. Tsay. 2000. "Sequence Analysis and Optimal Matching Methods in Sociology: Review and Prospect." *Sociological Methods and Research* 29:3.

Aisenbrey, S. and A. E. Fasang. 2010a. "New Life for Old Ideas: The "Second Wave" of Sequence Analysis Bringing the "Course" Back into the Life Course." *Sociological Methods & Research* 38:420-62.

Aisenbrey, S. and A. E. Fasang. 2010b. "New Life for Old Ideas: The "Second Wave" of Sequence Analysis Bringing the "Course" Back into the Life Course." *Sociological Methods and Research* 38(3):420-62.

Akerlof, G. A. and R. E. Kranton. 2000. "Economics and Identity." *Quarterly journal of Economics* 115(3):715-53.

Andersen, P. K., O. Borgan, R. D. Gill, and N. Keiding. 2012. *Statistical Models Based on Counting Processes*. Springer Science & Business Media. Berlin/Heidelberg, Germany

Barban, N. 2013. "Family Trajectories and Health: A Life Course Perspective." *European Journal of Population/Revue européenne de Démographie* 29:357-85.

Barban, N. and F. C. Billari. 2012. "Classifying Life Course Trajectories: A Comparison of Latent Class and Sequence Analysis." *Journal of the Royal Statistical Society. Series C (Applied Statistics)* 61:765-84.

Behncke, S. 2012. "Does Retirement Trigger Ill Health?" *Health Economics* 21: 282-300.

Blake, H. and C. Garrouste. 2013. *Killing me softly: work and mortality among French seniors* (No. 13/25). HEDG, c/o Department of Economics, University of York.

Blossfeld, H. and G. Rohwer. 2002. "Techniques of Event History Analysis." In *Techniques of Event History Modeling. New Approaches to Causal Analysis*. Lawrence Erlbaum Associates, New Jersey, United States

Burdorf, A. 2010. "Is Early Retirement Good for Your Health?" *BMJ (Clinical Research Ed.)*. 341:c6089.

Charles, K. K. 2002. "Is Retirement Depressing? Labor Force Inactivity and Psychological Well-being in Later Life." Technical report, National Bureau of Economic Research, Cambridge, MA.

Coe, N. B. and M. Lindeboom. 2008. "Does Retirement Kill You? Evidence from Early Retirement Windows." Technical report, Tilburg University, Center for Economic Research, the Netherlands.

Coe, N. B. and G. Zamarro. 2011. "Retirement Effects on Health in Europe." *Journal of Health Economics* 30:77-86.

Cooke, M. 2006. "Policy Changes and the Labour Force Participation of Older Workers: Evidence from Six Countries." *Canadian Journal on Aging/La Revue canadienne du vieillissement* 25:387-400.

Crawford, M. P. 1972. "Retirement as a Psycho-social Crisis." *Journal of Psychosomatic Research* 16:375-80.

de Luna, X., I. Waernbaum, and T. S. Richardson. 2011. "Covariate Selection for the Nonparametric Estimation of an Average Treatment Effect." *Biometrika* 98(4): 861-75.

Eibich, P. 2015. Understanding the effect of retirement on health: Mechanisms and heterogeneity. *Journal of Health Economics* 43:1-12.

Ellwardt, L., T. van Tilburg, M. Aartsen, R. Wittek, and N. Steverink. 2015. "Personal Networks and Mortality Risk in Older Adults: A Twenty-year Longitudinal Study." *PLoS One* 10:e0116731.

Fasang, A. E. 2012. "Retirement Patterns and Income Inequality." *Social Forces* 90: 685-711.

Gabadinho, A., G. Ritschard, N. S. Mueller, and M. Studer. 2011. "Analyzing and Visualizing State Sequences in R with TraMineR." *Journal of Statistical Software* 40:1-37.

Goldberg, M., A. Leclerc, S. Bonenfant, J-F. Chastang, A. Schmaus, N. Kaniewski, and M. Zins. 2007. Cohort profile: the GAZEL Cohort Study. *International Journal of Epidemiology* 36(1):32-39.

Grossman, M. 1972. "The Demand for Health: A Theoretical and Empirical Investigation. *NBER New York*.

Guillemard, A.-M. and M. Rein. 1993. "Comparative Patterns of Retirement: Recent Trends in Developed Societies." *Annual Reviews in Sociology* 19: 469-503.

Halfon, N. and M. Hochstein. 2002. "Life Course Health Development: An Integrated Framework for Developing Health, Policy, and Research." *Milbank Quarterly* 80: 433-79.

Hallberg, D., P. Johansson, and M. Josephson. 2014. "Early Retirement and Post-retirement Health." IFAU Working Paper (2014:12), Institute for Evaluation of Labor Market and Education Policy, Uppsala, Sweden.

Han, S.-K. and P. Moen. 1999. "Clocking Out: Temporal Patterning of Retirement." *American Journal of Sociology* 105:191-236.

Havighurst, R. J. 1954. “Flexibility and the Social Roles of the Retired.” *American Journal of Sociology* 59(4):309-11.

Holt-Lunstad, J., T. B. Smith, and J. B. Layton. 2010. “Social Relationships and Mortality Risk: A Meta-analytic Review. *PLoS Medicine* 7:e1000316.

Hult, C., M. Stattin, U. Janlert, and B. Järvholm. 2010. “Timing of Retirement and Mortality—A Cohort Study of Swedish Construction Workers.” *Social Science & Medicine* 70:1480-6.

Imai, K., G. King, and E. A. Stuart. 2008. “Misunderstandings between Experimentalists and Observationalists about Causal Inference.” *Journal of the Royal Statistical Society Series A, (Statistics in Society)* 171(2):481-502.

Insler, M. 2014. “The Health Consequences of Retirement.” *Journal of Human Resources* 49:195-233.

Johnson, J. V. and E. M. Hall. 1988. “Job Strain, Work Place Social Support, and Cardiovascular Disease: A Cross-sectional Study of a Random Sample of the Swedish Working Population.” *American Journal of Public Health* 78:1336-42.

Kohli, M. 1991. *Time for Retirement. Comparative Studies of Early Exit from the Labor Force*. Cambridge University Press, Cambridge, UK

Kohli, M. and M. Rein. 1991. “The Changing Balance of Work and Retirement.” Pp. 1-35 in *Time for Retirement: Comparative Studies of Early Exit from the Labor Force*, edited by Martin Kohli, Martin Rein, Anne-Marie Guillemard, Herman van Gunsteren. Cambridge: Cambridge University Press.

Kruskal, J. 1983. “An Overview of Sequence Comparison: Time Warps, String Edits, and Macromolecules.” *SIAM Review* 25:201-37.

Kuhn, A., J.-P. Wuellrich, and J. Zweimüller. 2010. “Fatal Attraction? Access to Early Retirement and Mortality.” *Institute for the Study of Labor (IZA) Discussion Paper 5160*.

Lesnard, L. 2006. “Optimal Matching and Social Sciences.” CREST-INSEE Working paper. Institut National de la Statistique et des Etudes Economiques, Paris.

Levenshtein, V. I. 1965. “Binary Codes Capable of Correcting Deletions, Insertions, and Reversals.” *Soviet Physics. Doklady* 10:707-10.

Lindeboom, M. and H. L. Andersen. 2010. “The Impact of Early Retirement on Health.” Available at SSRN: https://ssrn.com/abstract=1672025

Malmberg, G., L.-G. Nilsson, and L. Weinehall. 2010. “Longitudinal Data for Interdisciplinary Ageing Research. Design of the Linnaeus Database.” *Scandinavian Journal of Public Health* 38:761-7

Mazzonna, F. and F. Peracchi. 2012. Ageing, cognitive abilities and retirement. *European Economic Review* 56(4):691-710.

Mazzonna, F. and F. Peracchi. 2017. Unhealthy retirement?. *Journal of Human Resources* 52(1):128-51.

Mein, G., P. Martikainen, H. Hemingway, S. Stansfeld, and M. Marmot. 2003. “Is Retirement Good or Bad for Mental and Physical Health Functioning? Whitehall

II Longitudinal Study of Civil Servants." *Journal of Epidemiology and Community Health* 57:46-49.

Neuman, K. 2008. "Quit Your Job and Get Healthier? The Effect of Retirement on Health." *Journal of Labor Research* 29:177-201.

Neyman, J. 1934. "On the Two different Aspects of the Representative Method: The Method of Stratified Sampling and the Method of Purposive Selection." *Journal of the Royal Statistical Society A* 97:558-606.

Packard, M. D. 1982. "Retirement Options under the Swedish National Pension System." *Social Security Bulletin* 45:12.

Palme, M., et al. 1999. "Social Security, Occupational Pensions, and Retirement in Sweden." Pp. 355-402 in *Social Security and Retirement around the World*, edited by Jonathan Gruber and David A. Chicago, United States: Wise University of Chicago Press.

Palmer, E. E. 2000. *The Swedish Pension Reform Model: Framework and Issues*. Washington, DC: World Bank.

Piccarreta, R. and F. C. Billari. 2007. "Clustering Work and Family Trajectories by Using a Divisive Algorithm." *Journal of the Royal Statistical Society Series A (Statistics in Society)* 170:1061-78.

Reimers, C. and M. Honig. 1993. "The Perceived Budget Constraint under Social Security: Evidence from Reentry Behavior." *Journal of Labor Economics* 184-204. 11(1, Part 1), 184-204.

Rosenbaum, P. R. and D. B. Rubin. 1983. "The Central Role of the Propensity Score in Observational Studies for Causal Effects." *Biometrika* 70:41-55.

Rubin, D. B. 1973. "The Use of Matched Sampling and Regression Adjustment to Remove Bias in Observational Studies." *Biometrics* 185-203.

Rubin, D. B. 1990. "Comment: Neyman (1923) and Causal Inference in Experiments and Observational Studies." *Statistical Science* 5:472-80.

Rubin, D. B. 1991. "Practical Implications of Modes of Statistical Inference for Causal Effects and the Critical Role of the Assignment Mechanism." *Biometrics* 1213-1234.

Ruhm, C. J. 1990. "Bridge Jobs and Partial Retirement." *Journal of Labor Economics* 8(4):482-501.

Selén, J. and A.-C. Ståhlberg. 2007. "Why Sweden's Pension Reform Was Able to Be Successfully Implemented." *European Journal of Political Economy* 23: 1175-84.

Sjösten, N., M. Kivimäki, A. Singh-Manoux, J. E. Ferrie, M. Goldberg, M. Zins, J. Pentti, H. Westerlund, and J. Vahtera. 2012. "Change in Physical Activity and Weight in Relation to Retirement: The French Gazel Cohort Study." *BMJ Open* 2: e000522.

Skoog, G. R. and J. E. Ciecka. 2010. "Measuring Years of Inactivity, Years in Retirement, Time to Retirement, and Age at Retirement within the Markov Model." *Demography* 47:609-28.

Stenberg, A., X. de Luna, and O. Westerlund. 2012. "Can Adult Education Delay Retirement from the Labour Market?" *Journal of Population Economics* 25: 677-96.

Stuart, E. A. 2010. "Matching Methods for Causal Inference: A Review and a Look Forward." *Statistical Science* 25(1):1.

Therneau, T. M. 2015. *A Package for Survival Analysis in S*, Version 2.38. (http:// CRAN. R-project. org/package= survival).

Vahtera, J., H. Westerlund, M. Hall, N. Sjösten, M. Kivimäki, P. Salo, J. E. Ferrie, M. Jokela, J. Pentti, A. Singh-Manoux, A. Manoux, M. Goldberg, and M. Zins. 2009. "Effect of Retirement on Sleep Disturbances: The Gazel Prospective Cohort Study." *Sleep* 32:1459.

Vaupel, J. W. 2006. "Redistributing Work in Aging Europe." *Science* 312:1911-3.

Waernbaum, I. 2010. "Propensity Score Model Specification for Estimation of Average Treatment Effects." *Journal of Statistical Planning and Inference* 140: 1948-56.

Westerlund, H., M. Kivimäki, A. Singh-Manoux, M. Melchior, J. E. Ferrie, J. Pentti, M. Jokela, C. Leineweber, M. Goldberg, M. Zins, and J. Vahtera. 2009. "Self-rated Health before and after Retirement in France (Gazel): A Cohort Study." *The Lancet* 374:1889-96.

Westerlund, H., J. Vahtera, J. E. Ferrie, A. Singh-Manoux, J. Pentti, M. Melchior, C. Leineweber, M. Jokela, J. Siegrist, M. Goldberg, M. Zins, and M. Kivimäki. 2010. "Effect of Retirement on Major Chronic Conditions and Fatigue: French Gazel Occupational Cohort Study." *BMJ* 341:c6149.

Zins, M., A. Guéguen, M. Kivimaki, A. Singh-Manoux, A. Leclerc, J. Vahtera, H. Westerlund, J. E. Ferrie, and M. Goldberg. 2011. "Effect of Retirement on Alcohol Consumption: Longitudinal Evidence from the French Gazel Cohort Study." *PLoS One* 6:e26531.

## Author Biographies

**N. Barban** is a senior research associate in sociology and fellow of Nuffield College at the University of Oxford, United Kingdom. His research interests include quantitative methods in social sciences, life course analysis, demography and sociogenomics.

**X. de Luna** is professor in statistics at the Umeå School of Business, Economics and Statistics, Umeå University. His research interests include development of methods for causal inference in observational studies and for incomplete data, as well as

applications in the social and health sciences using population wide record linked registers and other longitudinal studies.

**E. Lundholm** is senior lecturer (associate professor) at the Department of Geography and Economic History and affiliated with Centre for Demographic and Ageing Research (CEDAR) at Umeå University. Her research focuses on migration, population ageing and family networks from a geographical perspective.

**I. Svensson** is a senior lecturer (associate professor) at the Umeå School of Business, Economics and Statistics, Umeå University. Her research interests cover sequence analysis, EM-algorithm, and applications in the social and forestry sciences.

**F. C. Billari**, FBA is professor of demography, Department of Policy Analysis and Public Management and DONDENA, Bocconi University, Milan, Italy. His main interest is the study of population, family and the life course.