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Bachelor Thesis BSC^2 Econometrics/Economics

The Relationship between Retirement and Socio-economic Position

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Abstract

This research investigates the relationship between retirement timing, the availability of pathways towards retirement and socio-economic position. Three indicators of socio-economic position are used: the European Socio-economic Classification (ESec), the Standard International Occupational Prestige Scale (SIOPS) and the International Socio-Economic Index of occupational status (ISEI). Using two samples of the Survey of Health, Ageing and Retirement in Europe (SHARE) and a piecewise-constant exponential model, a clear social gradient in retirement timing is established. Members of the petit bourgeoise, higher salariat and agricultural self-employed, together with workers in occupations with high prestige or high social status often retire late. Furthermore, workers in physically demanding jobs are found to retire more often involuntarily.

Contents

1 Introduction

Socio-economic position does not only directly affect health and mortality (Lynch & Kaplan, 2000; Wilkinson, 1997), but it also influences other aspects of life. One of those is retirement (Radl, 2012). Socio-economic position influences, among others, the accessibility to early retirement benefits and the probability of health problems, disability and unemployment. Retirement is an important event in the life of the elderly that has long-lasting consequences. Although no conclusive evidence has been found about the effect of retirement on well-being, it is important that problem groups are identified (Kim & Moen, 2002; Van Solinge & Henkens, 2008). This could, for example, include workers in low-income, physically demanding jobs. They have low wealth and run a high risk of disability and unemployment in older age (Visser, Gesthuizen, Kraaykamp, & Wolbers, 2016). Therefore, research on the relationship between socio-economic position and retirement can help policymakers in the decision-making process regarding retirement age and benefits.

Previous research has found that there exist clear social gradients in retirement timing (Blossfeld, Buchholz, & Kurz, 2011; Micheel, Roloff, & Wickenheiser, 2011). Radl (2012) emphasises that social class has an important effect on retirement timing and the pathways towards retirement. Blue-collar workers often retire early because of disability or financial incentives. In contrast, routine workers, self-employed workers and members of the service class often retire late. However, most of this research uses a narrow definition of socio-economic position, which only takes one or a few class determinants into account.

This leads to the following research question: what is the relationship between socio-economic position and the timing of retirement, and how does it influence the extent to which retirement is voluntary versus forced? Socio-economic position will be classified using the European Socio-economic Classification (ESeC), the Standard International Occupational Prestige Scale (SIOPS) and the International Socio-Economic Index of occupational status (ISEI). This leads to a broader definition of socio-economic position that takes into account a wide variety of indicators.

This research makes use of data from the Survey of Health, Ageing and Retirement (SHARE), waves 1 to 7. Based on an event history model, the influence of social stratification on retirement timing and whether withdrawal of work is voluntary or forced will be assessed. First, the research of Radl (2012) is replicated using a piecewise-constant exponential model. Then, this will be extended by not only considering socio-economic position at the time of retirement but also its effects over-time, using various definitions.

In the remainder of this paper, first, the theoretical framework and relevant literature will be summarised in Section 2. Sections 3 and 4, respectively, discuss the data and methodology that is used. The results of the research are presented in Section 3. This paper finishes with a conclusion in Section 6.

2 Theoretical framework

This section discusses the available literature on socio-economic position and retirement. First, several classification scales are discussed in Section 2.1. Then, a general framework for retirement decisions is described in Section 2.2. This section concludes with an overview of relevant literature on the relationship between socio-economic position and retirement.

2.1 Socio-economic classification of occupational position

There are at least three types of scales commonly used for the measurement of social stratification due to occupational position (Ganzeboom, De Graaf, & Treiman, 1992). The first type measures social status by prestige ratings of occupations. An example of this is the Standard International Occupational Prestige Scale (SIOPS) constructed by Treiman (1977). Another type of scale is the European Socio-economic Classification (ESeC), which is formed from sociologically derived classes based on employment relations (Rose & Harrison, 2007). Finally, there are occupational scales based on socio-economic status. An example of this is the International Socio-Economic Index of occupational status (ISEI) developed by Ganzeboom et al. (1992). Although these measures are highly correlated, they are conceptually different and are constructed in fundamentally distinct ways (Ganzeboom & Treiman, 1996). A first difference is that SIOPS and ISEI are continuous scales based on empirical data, while ESeC is categorical and has a sociological basis.

SIOPS is a prestige measure, which assumes that occupational status is the most important determinant of social position. It is based on average prestige scores from local and national prestige studies, covering more than 60 countries. In contrast with this, ESeC is derived from the Erikson-Goldthorpe-Portocarero (EGP) scheme (see Erikson & Goldthorpe, 1992). Occupations are categorised based on the amount of position-specific skills and knowledge needed and the degree to which the amount and quality of work can be monitored easily. This leads to a division of occupations into nine classes (see Table 1). The order of these classes is not hierarchical, as it gives a qualitative classification. Finally, ISEI tries to measure how the ability to transform education level in income is influenced by occupational structure. Therefore, it is based on the weighted average of education and income levels for each occupation.

Table 1: Classes of the European Socio-economic Classification

	ESeC class	Class name
1	Large employers, higher grade professional, administrative and managerial occupations	Higher salariat
2	Lower grade professional, administrative and managerial occupations and higher grade technician and supervisory occupations	Lower salariat
3	Intermediate occupations	Higher grade white-collar workers
4	Small employer and self-employed occupations (excl. agriculture etc.)	Petit bourgeois
5	Self-employed occupations (agriculture etc.)	Agricultural self-employed
6	Lower supervisory and lower technician occupations	Higher grade blue-collar workers
7	Lower services, sales and clerical occupations	Lower grade white-collar workers
8	Lower technical occupations	Skilled workers
9	Routine occupations	Semi- and non-skilled workers

Source: Rose and Harrison (2007)

2.2 Retirement timing

As a theoretical approach, the life cycle model can be used to model the decision when to retire. It assumes individuals maximise their utility by choosing between working and by that earning wage, or retiring and spending time in leisure. Following the notation and description of Stock and Wise (1990), indirect utility at time t, given retirement at time r, is denoted by $V_t(r)$, which is defined as

$$V_t(r) = \sum_{s=t}^{r-1} \beta^{s-t} U_W(Y_s) + \sum_{s=r}^{S} \beta^{s-t} U_R(B_s(r)). \tag{1}$$

Here, S is the year of death and Y_s is the wage when working in year s, with associated utility $U_W(Y_s)$. When retired in year s, $B_s(r)$ is the amount of retirement benefits that will be received with associated utility $U_R(B_s(r))$. As the amount of benefits will depend on the number of years worked, B_s is a function of r. Furthermore, β is a discount rate. An individual will retire at age r that maximises $V_t(r)$.

This specification allows for the inclusion of variables that influence retirement timing, like health status, family relations, institutional arrangements and other variables, by incorporating them in the utility functions. Many of these variables have been found to influence the retirement decision. Initial econometric research on retirement mainly focused on financial incentives, like the eligibility for Social Security and employer pensions (Quinn & Burkhauser, 1994). Later, a discussion arose whether push or pull factors are more important in determining retirement timing (Shultz, Morton, & Weckerle, 1998). Push factors push workers from the labour market towards retirement, while pull factors pull workers towards retirement. De Preter, Van Looy, and Mortelmans (2013) divided push and pull factors into micro- and macro-level influence. At a micro-level, important push factors are the health of an employee and dislike of the job. Examples of micro-level pull factors are the expectations of life after retirement and the desire to pursue hobbies or other activities. Macro-level push factors are restrictive labour market opportunities for the elderly, while macro-level pull factors are aspects like Social Security benefits and economic incentives. Consensus has been reached that both push and pull factors play a role in the retirement timing of elderly (Schils, 2008; Shultz et al., 1998; Vickerstaff & Cox, 2005).

2.3 Retirement and social stratification

Both push and pull factors also play a role in the relationship between socio-economic position and retirement. Previous research on this topic has mainly focused on socio-economic and job characteristics. Komp, van Tilburg, and van Groenou (2010) found that education level and wealth influence the necessity, possibility and desirability of working at an older age. Both a higher education level and larger wealth lead to a larger probability of continuing working for men. However, for women, those variables were not found to be significant. Meanwhile, Micheel et al. (2011) concluded that a higher income leads to earlier retirement.

Recently, research has investigated how the retirement decision is influenced by social class. Two volumes edited by Blossfeld and colleagues (Blossfeld, Buchholz, & Hofäcker, 2006; Blossfeld et al., 2011) reported that members of the working class retire earlier than self-employed workers and members of the service class. Visser et al. (2016) argue this is due to members of the working class running higher risks of disability and unemployment. This is confirmed by the research of Chirikos and Nestel (1991) and Blekesaune and Solem (2005) who conclude that workers in physically demanding jobs are more likely to retire early, and more often with disability retirement.

Radl (2012) studied the effects of social stratification and gender on retirement timing and accessibility to different pathways to retirement. Using a piecewise constant exponential model, he analysed data from the first wave of SHARE for 11 countries. He found that socio-economic position, classified by ESeC, influences the retirement decision significantly. Furthermore, the effects of employment constraints and economic incentives differed by class. Skilled manual workers and higher grade blue-collar workers often retire early because of disability risks and financial incentives. In contrast, the service class and self-employed workers often retire late. For the service class, this is mainly because there is not much involuntary exit. Routine workers also often retire late, if they do not retire involuntary due to disability. No significant differences in the effects of social class were found between men and women. Still, women often retire earlier because of their lower social class position.

Both Micheel et al. (2011) and Wahrendorf, Dragano, and Siegrist (2012) used another social classification scale, SIOPS, to study retirement timing. Micheel et al. (2011) found that workers with higher professional status are more willing to continue working in pensionable age. This effect was larger for women than for men. Also, Wahrendorf et al. (2012) concluded that a clear social gradient exists in early retirement intentions. They used not only occupational prestige, but also occupational class, measured by the EGP scheme, and occupational skill level. For all these measures of occupational position, it was found that workers in a lower position were more likely to report intentions to retire as early as possible.

From this previous research, we can conclude that many factors influence the decision to retire. Socio-economic position is one of them. Even though there exists a wide variety of measures of occupational position, they all indicate there exists a social gradient in retirement timing. Not all workers can afford to retire when they would like to, and members of some social classes more often have to retire involuntarily. This paper contributes to this literature by considering a broad variety of indicators of socio-economic position and their relation to retirement timing.

3 Data

To answer the research question, data is used from the Survey of Health, Ageing and Retirement in Europe (SHARE).[1] SHARE is a panel database of responses to surveys conducted in 27 European countries and Israel amongst elderly aged 50 years and above. Data has been collected over 7 waves from, in total, more than 140,000 participants.

[1]As a condition of use of the SHARE dataset, we note that, "This paper uses data from SHARE Waves 1, 2, 3, 4, 5, 6 and 7 (DOIs: 10.6103/SHARE.w1.700, 10.6103/SHARE.w2.700, 10.6103/SHARE.w3.700, 10.6103/SHARE.w4.700, 10.6103/SHARE.w5.700, 10.6103/SHARE.w6.700, 10.6103/SHARE.w7.700), see Börsch-Supan et al. (2013) for methodological details. The SHARE data collection has been primarily funded by the European Commission through FP5 (QLK6-CT-2001-00360), FP6 (SHARE-I3: RII-CT-2006-062193, COMPARE: CIT5-CT-2005-028857, SHARELIFE: CIT4-CT-2006-028812) and FP7 (SHARE-PREP: N°211909, SHARE-LEAP: N°227822, SHARE M4: N°261982). Additional funding from the German Ministry of Education and Research, the Max Planck Society for the Advancement of Science, the U.S. National Institute on Aging (U01_AG09740-13S2, P01_AG005842, P01_AG08291, P30_AG12815, R21_AG025169, Y1-AG-4553-01, IAG_BSR06-11, OGHA_04-064, HHSN271201300071C) and from various national funding sources is gratefully acknowledged (see www.share-project.org)."

3.1 Sample construction

3.1.1 Replication sample

For the replication of the work of Radl (2012), data of wave 1 of SHARE is used. Following his research, the analysis sample consists of all respondents that were born between 1930 and 1949. That is, respondents that were between 55 and 75 at the time of the first interview. Respondents from Israel were excluded, as the country is not part of Europe. Furthermore, respondents that never worked, or reported their current job situation as homemaker or 'other' were not considered. Also, if the occupation code of a respondent was homemaker, they were excluded.

Respondents became at risk of retirement from the age of 50. Here, retirement is understood as withdrawal from lifetime employment, instead of a definition based on eligibility for pension benefits. As the end of working life is one of the most important changes in later life, this is the most frequent used characterisation of retirement (Radl, 2014). Therefore, respondents are considered as retirees when they report themselves as retired or when they are permanently sick or disabled. Retirees who work more than 20 hours per week are considered as active. Furthermore, respondents for whom the year of retirement or the reason for retirement is unknown, are excluded from the sample. This results in a final replication sample of 12,208 respondents, of which 7,543 were retired at the time of the interview. They live in the countries Austria, Belgium, Denmark, France, Germany, Greece, Italy, the Netherlands, Spain and Switzerland. An overview of the number of removed respondents can be found in Table A1 in the Appendix.

3.1.2 Extension sample

Moreover, to extend the research of Radl (2012), a more recent data set is used that includes respondents from 18 European countries. The main sample is taken from the SHARE wave 7 survey. However, some questions are only asked in the baseline interview, that is, the first interview in which the respondent participates. Therefore, also data from all previous waves has to be used. The countries that are analysed are the same countries as used in the replication part, except the Netherlands, and with the addition of Croatia, Czech Republic, Estonia, Hungary, Luxembourg, Poland, Portugal and Slovenia. The results of the survey in the Netherlands of wave 7 are not published yet, as they participated in an own questionnaire. Therefore, they are excluded from this research.

Wave 7 of SHARE consists of a SHARELIFE interview and a regular interview. The SHARE-LIFE interview asks questions about the life and work history of respondents. It is answered by all respondents who did not participate in the SHARELIFE interview in wave 3. The analysis sample is restricted to those respondents of wave 7 that participated in the SHARELIFE interview in wave 3 or 7 and have answered at least one regular interview. In the retrospective life history interview in wave 3, only one digit ISCO codes for previous occupations were recorded. Therefore, the classifications of occupation have been imputed for these respondents (for details see Section 3.5).

Decisions regarding the sample construction have been made based on an attempt to select the sample in a similar way as in the replication part. Therefore, the sample was restricted to all respondents who were between 55 and 75 years old in 2017, the year of the first interview in wave 7. That is, respondents who were born between 1943 and 1962. This implies that there exists a slight overlap in respondents between the replication and extension sample, namely those respondents who were born between 1943 and 1949 and participated in both wave 1 and wave 7. Observations were excluded when a respondent never did any paid work or reported their occupational status in wave 6 or 7 as homemaker or 'other'. Retirees were excluded when their retirement year was unknown or they retired before the age of 50. This resulted in a final extension sample of 31,929 respondents, of which 20,315 were retired at the time of the interview. An overview of the number of removed respondents can be found in Table A1 in the Appendix.

3.2 Dependent variables

Following Radl (2012), the dependent variable of the main analysis is the number of years between the year the respondent turns 50 and the year of retirement.

Furthermore, in the second part of the analysis, a distinction needs to be made between forced and voluntary retirement. Adhering to the work of Radl (2012), respondents who are permanently ill or disabled are regarded as having retired involuntarily, as well as respondents who report that they retired due to ill health or were made redundant. All other respondents are categorised as having retired voluntarily. This distinction does not capture the whole complicated nature of retirement reason. However, it makes a clear distinction between voluntary and forced retirement that captures their nature.

3.3 Independent variables

3.3.1 Independent variables replication

For the replication part of the analysis, the explanatory variables proposed by Radl (2012) are used. Those are gender, ESeC class, family situation, number of grandchildren, years of education, job tenure, firm size and country of residence. Of these variables, family situation, number of grandchildren and job tenure are implemented as time-varying covariates. The reader is referred to Radl (2012) for further details on the construction of the variables.

Gender

Gender is used to account for gender differences in retirement patterns. Women often have a lower income over their work life and fewer opportunities for career development (Duncan & Loretto, 2004). Therefore, retirement opportunities are often better for men (Shuey & O'Rand, 2004). Still, women have been found to retire earlier, due to a lower class position (Radl, 2012). Therefore, an indicator for gender is included as a variable. It takes value 1 for females, and 0 otherwise.

ESeC classification

The European Socio-economic Classification (ESeC) is used to classify social position in nine classes. This variable is created based on the International Standard Classification of Occupation (ISCO-88) provided by SHARE and employment status. ISCO is a classification of occupations by the International Labour Organisation (ILO) based on skill level and specialisation needed to perform the job (International Labour Office, 1990). Jobs are divided into 10 major groups. Those are sub-divided in sub-major, minor and unit groups, resulting in 4-digit ISCO-codes. Moreover, information on employment status is needed to create ESeC classes. This variable indicates whether a respondent is an employee or self-employed. Furthermore, if a respondent is an employee, whether he or she is a supervisor, and when self-employed, the number of employees at the workplace. Both ISCO-88 code and employment status are based on the main job for respondents who are employed at the time of the interview. For unemployed and retired respondents, it is based on their last job. Respondents are classified using the conversion matrix provided by Harrison and Rose (n.d.).

Household context

Retirement intentions of couples are often correlated (Gustman & Steinmeier, 2004). Therefore, a time-varying variable is created that contains information on marital status, and employment situation of the partner when married. This variable consists of 7 categories: married, spouse employed; married, spouse retired; married, spouse homemaker; married, spouse missing; divorced; widowed and unmarried. The employment situation of a respondent's partner is not recorded in SHARE. However, if the partner also participates in SHARE, it can be tracked down using their employment situation. This leads to a relatively large share of respondents missing information on the employment status of the partner. A fourth category is made for married respondents of which the employment status of the partner is missing (22% of married respondents). Married respondents of which the spouse is employed are treated as the omitted category.

Number of grandchildren

The birth of a new grandchild has been found to increase the probability of retirement because of grandparents providing care for their grandchildren (Lumsdaine & Vermeer, 2015). Therefore, the number of grandchildren is used as a time-varying control variable. It is not exactly clear how Radl (2012) implemented this variable. Therefore, the following approach has been chosen. The number of reported grandchildren is used, except if the number of children is 0. Furthermore, if the sum of the number of children of each child is larger than the number of grandchildren, the former is used. If a respondent reports that the year in which the youngest child of one of the children is born is before the year of the interview, the number of grandchildren is decreased by one for the years before the year of birth. This specification ensures that the number of grandchildren can vary over time. Nevertheless, it tends to overestimate the number of grandchildren at the beginning of the period at risk, as only the year of birth of the youngest child of each child is known.

Country of residence

Country dummies are included to control for country-specific situations like institutional differences. Austria is treated as the omitted category.

3.3.2 Independent variables extension

For the extension, most variables of the replication have been used, together with some new measures of social class. The variables gender, number of grandchildren, years of education and country of residence are constructed in the same way as in the replication. Two new measures of social position and an indicator for health limitations are implemented as new variables. Finally, the variable firm size cannot be used, as no information on this was available in the SHARELIFE interview. Moreover, only in waves 1 and 7 information was available on the number of employees in the firm for respondents that were not self-employed. This led to more than 80% of observations missing data for the variable firm size. Hence, this variable is omitted.

ESeC codes

ESeC codes for social class have been constructed based on ISCO-08 codes instead of ISCO-88 codes, as those were the ones available in wave 7. The main aim of this update of the ISCO coding was to better reflect the technological changes in the labour market and to improve on shortcomings of the previous version (International Labour Office, 2012). Most changes took place at the minor and unit levels. Furthermore, because employment history is assessed in the SHARELIFE interview, social class can now be implemented as a time-varying covariate. Yet, there is only data available on whether a worker is employed or self-employed, not on his or her supervisory status. Therefore only a restricted employment status variable could be constructed, which consists of the categories: Self-employed, No employees, and Other employees. The data used in the replication part has been used to investigate whether it would be better to use the simplified ESeC, which is based only on ISCO codes, or to use the restricted employment status. The correspondence between ESeC classes using only ISCO codes and the full information was 77 %, while compared with the restricted employment status it was 86 %. Therefore, the restricted employment status variable has been used. When no information was available on self-employment status, workers were categorised as Other employees. Respondents are classified using the conversion matrix provided by Harrison, Eric (n.d.). ISCO codes that are not in this table are recoded to the closest existing main category.

Other measures of social classification

Next to ESeC codes, also SIOPS and ISEI codes have been constructed based on the four-digit ISCO-08 coding of occupations. For this, the conversion tools of (Ganzeboom, Harry B.G. and Treiman, Donald J, n.d.) are used. These variables are implemented as time-varying covariates. Non-existent ISCO codes are recoded to the closest existing main category. Because both SIOPS and ISEI are continuous measures, four categories have been created based on approximate quartiles, to gain further insights into the relationship between occupational position and retirement timing. The categories are: low (< 25), moderate (25-40), average (40 - 65) and high (65+). For both variables, the low category is treated as the omitted category.

Health limitations

To correct for the influence of health limitations on the retirement decision an indicator variable is created. This variable takes value 1 if a respondent reports that he or she has health problems that limit the kind or amount of paid work they can do, and 0 otherwise. It is implemented as a time-varying covariate.

3.4 Descriptive statistics

Summary statistics of both samples are displayed in Table 2. In the replication sample, there are slightly more males than females (59.3 % versus 40.8 %). This is probably due to the fact that more often females do not perform any paid work during their life than men, and are therefore excluded from the analysis. In the extension sample, this difference has disappeared, possibly because the women labour force participation has been increasing over time. Furthermore, it appears that respondents are not equally divided over social classes. Lower salariat is the largest class in the replication sample with 22.9 % of respondents, while only 4.4 % of respondents are agricultural self-employed. In the extension sample, the classes petit bourgeois, agricultural self-employed and higher grade blue-collar contain only a few observations (< 5% each). Also, the SIOPS classes vary in sample size, with most respondents having an average position (50.2 %). In contrast, respondents are almost equally divided over ISEI classes.

When it comes to family situation, a substantial proportion of married responses misses information on the employment status of the partner in both samples (around 20 %). Therefore, results regarding family situation should be interpreted with caution. Next, when looking to the reason for retirement, much more respondents retire voluntarily than forced in both samples. However, it should be noted that for 4,071 retirees (20.2 %) of the extension sample, the reason for retirement is not known. This should be taken into account when analysing the availability of pathways towards retirement. Finally, it can be noted that almost 20% of respondents of the extension sample suffer from health problems that limit the kind or amount of paid work they can do.

3.5 Missing values

In the final replication sample, 8.6% of respondents have missing values on one or more explanatory variables. The share of imputed values per variable is: job tenure (7.6%), firm size (4.5%), ESeC class (3.7%) and years of education (0.7%). In the final extension sample, 37.4% of the observations had missing values on one or more explanatory variables. The largest share of those (34.3%) was due to missing ISCO codes. However, for 13.3% of the total number of observations, one digit ISCO codes were available, which have been used as a variable in the imputation equations. For the other variables, the share of missing values per variable was: job tenure (3.0%), number of grandchildren (1.2%), and years of education (1.0%). For the variable number of grandchildren in the replication sample, the imputations provided by SHARE are used. The other missing values have been imputed using multiple imputation with chained equations. For details on the imputation process, see Appendix B.

Table 2: Summary statistics at the time of retirement or interview

Variable	Categories or range	Replication		Extension	
		% or mean(sd)	N	% or mean(sd)	N
Gender	Male	59.25%	7,239	47.97%	15,315
	Female	40.75%	4,978	52.03%	16,614
ESeC	Higher salariat	11.76%	1,383	18.88%	4,026
	Lower salariat	22.86%	2,689	14.44%	3,078
	Higher grade white-collar	8.91%	1,048	12.91%	2,752
	Petit bourgeois	9.95%	1,170	4.91%	1,047
	Agricultural self-employed	4.38%	515	2.11%	450
	Higher grade blue-collar	9.22%	1,085	0.79%	168
	Lower grade white-collar	7.97%	937	15.09%	3,218
	Skilled manual	8.88%	1,045	16.77%	3,575
	Semi- and non-skilled	16.07%	1,890	14.10%	3,006
SIOPS	Low prestige	-	-	13.81%	2,945
	Moderate prestige	-	-	30.77%	6,560
	Average prestige	-	-	50.19%	10,701
	High prestige	-	-	5.23%	1,114
ISEI	Low status	-	-	24.75%	5,276
	Moderate status	-	-	26.16%	5,578
	Average status	-	-	25.60%	5,458
	High status	-	-	23.49%	5,008
Family situation	Married, spouse employed	26.84%	3,279	27.31%	8,720
	Married, spouse retired	21.59%	2,638	23.39%	7,467
	Married, spouse homemaker	13.91%	1,699	5.07%	1,620
	Married, spouse missing	17.63%	2,154	20.71%	6,611
	Divorced	7.93%	969	11.69%	3,731
	Widowed	5.40%	660	5.19%	1,656
	Unmarried	6.70%	818	6.65%	2,124
Number of grandchildren	0-22	1.97 (2.54)	12,183	1.93 (2.38)	31,638
Years of education	0-21	10.46 (4.46)	12,129	11.81 (4.11)	31,622
Job tenure	0-67	25.01 (13.29)	12,188	27.20 (13.19)	31,038
Firm size	1-500+	16-24 empl	11,664	-	-
Reason for retirement	Voluntary	65.24%	4,921	76.74%	12,467
	Forced	34.76%	2,622	23.26%	3,778
Health limitations	No	-	-	80.07%	25,565
	Yes	-	-	19.93%	6,364

4 Methodology

4.1 Piecewise-constant exponential model

The life cycle model described in Section 2.2 is computationally complex and not very flexible (Belloni, 2008). It doesn't allow easily for modifications because it it is a structural model. Therefore, a proportional hazard model is used instead. Under strong restrictions, this is a special case of the option value model (Stock & Wise, 1990). Although this model is less forward-looking, it allows that the variables of interest can change over time.

Proportional hazard models are part of a group of models that are used in survival analysis.[2] That is, the time until an event occurs, here retirement, is modelled. Let T_i denote the time at which the event happens for individual i, with cumulative density function $F(t)$. Then, the probability of survival beyond time t is

$$S(t) = P[T_i > t] = 1 - F(t). \tag{2}$$

This is called the survival function. Furthermore, there is the hazard function which is a measure of risk. It is defined as

$$\lambda(t) = \frac{f(t)}{S(t)}, \tag{3}$$

where $f(t)$ is the probability density function of T_i. The hazard ratio measures the probability of the occurrence of an event in an infinitely small time period between t and $t + \delta t$ given that the individual has survived until time t. The hazard function when all covariates are zero is called the baseline hazard function.

A piecewise-constant exponential (PCE) model is used to model the survival data. This model is used because the specification of the baseline hazard function does not need to be imposed in advance. Time is divided into K intervals using cut-points $\tau_1, \tau_2, ...\tau_K$. The baseline hazard is constant within each interval but can vary between intervals. Then, the hazard function is given by

$$\lambda(t, X_t) = \begin{cases} \lambda_0(t_1)exp(X_1\beta) & t \in (0, \tau_1] \\ \lambda_0(t_1)exp(X_2\beta) & t \in (\tau_1, \tau_2] \\ \vdots & \\ \lambda_0(t_K)exp(X_K\beta) & t \in (\tau_{K-1}, \tau_K] \end{cases} \tag{4}$$

Here, $\lambda_0(t)$ is the baseline hazard function and $X_i, i = 1, ..., K$ is a vector of covariates with corresponding parameters β. The covariates may be fixed or time-varying between intervals. To

[2] What follows is based on Jenkins (2004).

be consistent with Radl (2012), time-intervals are based upon the most common institutional retirement ages in Europe: 50-54, 55-59, 60, 61-62, 63-64, 65 and 66+ years.

Parameters are estimated using maximum likelihood estimation. Assume that the sample consists of spells $j = 1, ..., J$, which are completed at time T_j, such that $T_j < t^*$, and spells $k = 1, ..., K$, which are right-censored and completed at time $T_k > t^*$. Then, the likelihood function is given by

$$\mathcal{L} = \prod_{j=1}^{J} f(t_j) \prod_{k=1}^{K} S(t^*), \quad (5)$$

where $f(T_j)$ is the probability density function of T_i and $S(t^*)$ the survival function at time t^*.

Each respondent has yearly observations. Therefore, Huber-White robust standard errors (Huber, 1967; H. White, 1980) are used to correct for the correlation that exists between the observations of an individual.

For the extension part, separate models are estimated for the three classifications of socio-economic position. The measures are highly correlated (correlation $> \pm 0.75$), therefore, joint estimation can suffer from multicollinearity (Mason & Perreault Jr, 1991). Because the variables share a substantial amount of information, partial effects cannot be separated. Furthermore, standard errors are inflated and the models tend to be unstable. Therefore, the effects the of the social classification measures are estimated separately.

For these analyses, the variable health limitations is excluded. Health problems is one of the reasons for forced retirement. If this variable is included, health differences due to social position will be ignored to some extent. Therefore, this variable is excluded from the analysis.

4.2 Competing risks framework

Competing risks exist when there are events which, if they occur, change the probability of occurrence of the event of interest.[3] The accessibility of different pathways to retirement can be assessed using a competing risk framework that distinguishes between forced and voluntary retirement. If the event of interest is voluntary retirement, forced retirement can be seen as a competing risk. Namely, if a respondent retires involuntarily, the probability of retiring voluntarily becomes 0, and vice versa.

Because in this research we are interested in estimating effect sizes, cause-specific hazard models seem to be most suitable for estimating the competing risks framework. This means that separate proportional hazard models are estimated for voluntary and forced retirement. In these models, respondents who experience the competing event are treated as censored at the time

[3] What follows is based on Noordzij et al. (2013).

of the event. Then, the estimated hazard ratios can be interpreted as the hazard of the event among those respondents which did not yet experience the event or the competing event.

4.3 Sampling weights

In his research, Radl (2012) uses calibrated sampling weights, provided by SHARE, such that the sample is representative for the elderly population of Western Europe. Here, the choice is made to not include sampling weights in the extension. Solon, Haider, and Wooldridge (2015) argue that weighting to create a representative sample is necessary when estimating population descriptive statistics. For causal inference, weights can be used to correct for heteroskedasticity related to population size, to correct for endogenous sampling, or when estimating average partial effects. SHARE tries to sample a representative sample. As only a small proportion of respondents is excluded due to missing values, the sample is expected to be still representative. Furthermore, because the sampling design of SHARE varies by country, the effects of including weights are not straightforward. Therefore, sampling weights are not included in the extension. Still, the weights are used in the replication analysis to stay as close as possible to the original research.

The calibrated cross-sectional weights provided by SHARE are used, together with the primary stratum and sampling unit. If the primary stratum was missing, country-specific subsamples were used. Furthermore, if there was no primary sampling unit available, the sampling unit was assumed to be individuals. Note that although only a subpopulation of the total sample in wave 1 is used, the estimates of the variance are based on the whole sample.

5 Results

5.1 Effect of social position on retirement timing

5.1.1 Hazard ratios for replication sample

Table 3 contains the estimated hazard ratios of the piecewise-constant exponential model for retirement timing. Hazard ratios larger than 1 indicates that an individual is more likely to retire with higher values of the explanatory variable. Conversely, a hazard ratio that is smaller than 1 means that an individual is less likely to retire. Model 1 controls for gender, social class and family situation, while Model 2 also accounts for number of grandchildren, years of education, job tenure and firm size.

Model 1 shows that the retirement timing of females does not differ significantly from men, all else equal. In contrast to this, there are clear class differences in work exit. The higher salariat and agricultural self-employed are 25 % less likely to retire than semi- and non-skilled workers.

The petit bourgeois has the smallest probability of retirement (45 % less). At the same time, the higher grade blue-collar and skilled manual class have a more than 20% higher likelihood of retirement.

Table 3: Hazard ratios of piecewise-constant exponential model of retirement timing for the replication sample

			Radl (2013)	
	Model 1	Model 2	Model 1	Model 2
Female	1.00	1.09**	1.00	1.07
ESeC (ref: semi- and non-skilled)				
Higher salariat	0.75***	0.79***	0.74***	0.75***
Lower salariat	0.94	0.96	0.97	0.96
Higher grade white-collar	1.11	1.13*	1.11	1.10
Petit bourgeois	0.55***	0.73***	0.58***	0.55***
Agricultural self-employed	0.75***	0.81**	0.72***	0.56***
Higher grade blue-collar	1.25***	1.24***	1.28***	1.19**
Lower grade white-collar	1.04	1.10	1.09**	1.13***
Skilled manual	1.22***	1.20***	1.22***	1.17**
Family situation (ref: married, spouse employed)				
Married, spouse retired	1.89***	1.85***	1.82***	1.79***
Married, spouse homemaker	1.21***	1.18***	1.18***	1.12
Married, spouse missing	1.28***	1.25***	1.24***	1.21***
Divorced	1.15**	1.19***	1.17*	1.26***
Widowed	1.31***	1.29***	1.26***	1.27***
Unmarried	1.14**	1.17**	1.14***	1.13***
Number of grandchildren	-	1.02**	-	1.02**
Years of education	-	0.97***	-	0.98***
Job tenure	-	1.01***	-	1.02***
Firm size	-	1.15***	-	1.00***

*p<0.1; **p<.05; ***p<.01

When considering family situation, it appears that married respondents with a partner that is employed retire later than all other respondents. Especially, married couples of which the spouse is already retired are much more likely to retire (89 %). This is in line with earlier research (Johnson, 2004; Kim & Moen, 2002).

Turning now to Model 2, the results do not change much. Most effect sizes become slightly smaller when controlling for number of grandchildren, years of education, job tenure and firm size. A noteworthy difference is found for the variable gender. Now, females are 9 % more likely to retire than men, and this difference is significant. Furthermore, respondents with more grandchildren retire slightly earlier, *ceteris paribus*. Respondents with more years of education retire later (3 %). In contrast, both a longer job tenure and a larger firm size are associated with earlier retirement.

5.1.2 Comparison with Radl (2012)

The results described above are based on the replication of the work of Radl (2012). Although, I have tried to stay as close as possible to the original research, there are some slight deviations. For most covariates, the effect sizes and significance level differ only to a small degree (see Table 3, the last 2 columns). One of the most striking departures is the difference in significance level for gender in model 2. Even though the coefficients are very similar, females do retire significantly earlier than men according to this research, at a 5 % significance level, but not according to Radl (2012). Another difference is found for the petit bourgeois and agricultural self-employed in Model 2. While Radl (2012) reports an estimated hazard ratio of about 0.55 in both models, in the replication, it was found to be, respectively, 0.73 and 0.81. Moreover, Radl (2012) concludes that lower grade white-collar workers retire significantly earlier than semi- and non-skilled worker. However, in this research, the difference was not found to be significant in both Models 1 and 2, even though the estimated hazard ratios are relatively close. Another deviation can be found with regards to married respondents with a spouse that is homemaker in Model 2. The hazard ratio is significantly different from 1 in this research, but not in that of Radl (2012). Finally, the difference in the hazard ratio of firm size is noteworthy. Both analysis report that respondents working in a larger firm are more likely to retire. However, according to Radl (2012) the effect size is close to zero, while in the replication is was found to be 15 %.

There are several possible reasons for these slightly deviating results. A first difference can be found in the sample size. This research has a final analysis sample which contains 12,208 observations of which 7,543 are retired. In contrast with this, the sample of Radl (2012) has slightly fewer observations, 12,154 of which 7,527 are already retired. This difference in observations leads to a somewhat larger proportion of missing values in this research. Furthermore, missing values have been imputed, which introduces a random element in the data. Finally, these differences could be due to deviations in the construction of variables. For example, it is not completely clear how Radl (2012) constructed the variable number of grandchildren. Moreover, the exact implementation of the sampling weights cannot be deduced from his paper. This could have introduced the above-described differences.

5.1.3 Hazard ratios for the extension sample

Table 4 shows the estimated hazard ratios of the PCE model using the different classifications of socio-economic position for the extension sample. Separate models have been estimated for social class, position and status. All hazard ratios and significance levels for the control variables are very similar. First, in all models females are found to be more than 25 % more likely to retire than men. This difference is much larger than for the extension sample, in which only a difference of 9 % was found.

Turning to social class, the results show that all classes, except higher grade blue-collar and skilled manual workers, retire significantly later than semi- and non-skilled workers in Model 1. The probability of retirement is smallest for the petit bourgeois (44 % less) and agricultural self-employed (35 % less). Only higher grade blue-collar workers retire earlier, but this difference is not significant. Results do not differ much between Model 1 and Model 2, except for the higher grade white-collar class. In Model 1, they retire 9 % later than semi- and non-skilled workers. But after controlling for number of grandchildren, years of education, job tenure and health limitations, they retire earlier, although the difference is not significant.

Also, when looking to occupational prestige, a clear social gradient is found. Workers with low occupational prestige have a 12 % higher probability of retiring than those with average prestige. Compared to workers with high prestige, the difference is 31 %. However, the difference decreases when controlling for number of grandchildren, years of education, job tenure and health limitations. Especially this last variable has a large influence on early retirement, as could be expected. Then, only the difference between low prestige and high prestige is significant (19 %).

For socio-economic status, similar results are found in Model 1. Again workers with a low or moderate status retire first. Workers with a higher status retire later, even when controlling for health limitations. Those with average status retire 6 % later and those with high status 21 %. However, when controlling for number of grandchildren, years of education, job tenure and health limitations, workers with an average status are found to retire 5 % earlier than those with a low status. This difference is significant at a 10 % significance level. Also, the difference between the retirement probability of those with low and high status has become much smaller. Now it is only 6 %.

The effects of family situation, number of grandchildren, years of education, job tenure and health limitations on retirement timing are approximately the same for all six models. Again, married respondents with a spouse that is employed retire significantly later than all other married or widowed respondents. Especially married individuals of which the partner is already retired, have a high probability of retirement (45 % more). Furthermore, divorced and unmarried

Table 4: Hazard ratios of piecewise-constant exponential model of retirement timing of the extension sample

	Social class		Social prestige		Social status	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Female	1.24***	1.21***	1.25***	1.23***	1.25***	1.24***
ESeC (ref: semi- and non-skilled)						
Higher salariat	0.73***	0.86***	-	-	-	-
Lower salariat	0.80***	0.90***	-	-	-	-
Higher grade white-collar	0.91***	1.02	-	-	-	-
Petit bourgeois	0.56***	0.61***	-	-	-	-
Agricultural self-employed	0.65***	0.62***	-	-	-	-
Higher grade blue-collar	1.06	1.10	-	-	-	-
Lower grade white-collar	0.91***	0.98***	-	-	-	-
Skilled manual	0.99	0.96***	-	-	-	-
SIOPS (ref: low prestige)						
Moderate prestige	-	-	0.99	1.00	-	-
Average prestige	-	-	0.88***	0.96	-	-
High prestige	-	-	0.69***	0.81***	-	-
ISEI (ref: low status)						
Moderate status	-	-	-	-	0.98	1.02
Average status	-	-	-	-	0.94***	1.05*
High status	-	-	-	-	0.79***	0.94**
Family situation (ref: married, spouse employed)						
Married, spouse retired	1.45***	1.40***	1.46***	1.41***	1.46***	1.41***
Married, spouse homemaker	1.33***	1.27***	1.31***	1.25***	1.31***	1.25***
Married, spouse missing	1.15***	1.13***	1.14***	1.12***	1.14***	1.13***
Divorced	1.04	1.04	1.04	1.04*	1.04	1.05**
Widowed	1.30***	1.25***	1.31***	1.26***	1.31***	1.26***
Unmarried	1.02	1.03	1.02	1.02	1.03	1.03
Number of grandchildren	-	1.02***	-	1.02***	-	1.02***
Years of education	-	0.98***	-	0.98***	-	0.98***
Job tenure	-	1.01***	-	1.01***	-	1.01***
Health limitations	-	1.40***	-	1.39***	-	1.40***

*p<0.1; **p<.05; ***p<.01

respondents do not retire significantly earlier than married respondents with an employed spouse in most models. Finally, respondents who reported health problems that limit the kind or amount of work they can do, have a much larger probability of retiring than those without (about 40 %).

5.1.4 Comparison of results between replication and extension sample

As already noted above, a first difference between results for the replication and extension sample can be found for the hazard ratios for gender. In the replication sample, females were only 9 % more likely to retire after controlling for number of grandchildren, years of education, job tenure and firm size. Contrasting with this, females were found to be 20 to 25 % more likely to retire in the extension sample in all models. It should be noted that the proportion of females in the replication sample is about 40 %, while it is 52 % in the extension sample. This suggests an increase in workforce participation of women over time. Moreover, it indicates that although a larger proportion of women performs paid work, they retire earlier than men.

For both samples, the probability of retirement was smallest for the petit bourgeois, followed by agricultural self-employed and the higher salariat (25 % to 50 % less than semi- and non-skilled). In the replication sample, higher grade blue-collar and skilled manual workers had a more than 20 % larger probability of retirement than semi- and non-skilled workers. In contrast to this, in the extension sample, the difference was not significant. When comparing the effect of family situation, it appears that hazard ratios were smaller in the extension sample. While in the replication sample, married respondents of whom the spouse was retired were more than 80 % more likely to retire, in the other sample it was found to be about 40 %. The difference for divorced and unmarried respondent also reduced and became insignificant relative to married respondents of whom the spouse was employed.

5.1.5 Comparison of West-Europe with the whole of Europe

Part of the difference between the results of the replication and extension sample could be due to number of the countries that is part of the sample. The replication sample exists of respondents from 11 countries from Western Europe, while the extension sample also contains participants from countries in Central and Eastern Europe, like Czech Republic, Estonia and Hungary. Therefore, the piecewise-constant exponential model has been estimated for the extension sample, only including the countries that are part of the replication sample. The final sample of this estimation consists of 20,284 respondents of which 12,306 respondents were retired at the time of the interview. They come from 10 West-European countries, as the Netherlands was not part of the survey in wave 7 of SHARE. The results of this estimation are displayed in Table 5.

Table 5: Hazard ratios of PCE model of retirement timing for the restricted extension sample

	Social class		Social prestige		Scoial status	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Female	1.02	1.00	1.05**	1.04**	1.05**	1.04**
ESeC (ref: semi- and non-skilled)						
Higher salariat	0.76***	0.89**	-	-	-	-
Lower salariat	0.86***	0.95	-	-	-	-
Higher grade white-collar	0.99	1.06	-	-	-	-
Petit bourgeois	0.54***	0.57***	-	-	-	-
Agricultural self-employed	0.66***	0.63***	-	-	-	-
Higher grade blue-collar	1.22	1.27	-	-	-	-
Lower grade white-collar	0.94	0.99	-	-	-	-
Skilled manual	0.96	0.91*	-	-	-	-
SIOPS (ref: low prestige)						
Moderate prestige	-	-	0.98	0.98	-	-
Average prestige	-	-	0.92**	0.98	-	-
High prestige	-	-	0.74***	0.84***	-	-
ISEI (ref: low status)						
Moderate status	-	-	-	-	1.01	1.05
Average status	-	-	-	-	1.01	1.10***
High status	-	-	-	-	0.88***	1.03
Family situation (ref: married, spouse employed)						
Married, spouse retired	1.50***	1.47***	1.52***	1.48***	1.52***	1.48***
Married, spouse homemaker	1.25***	1.20***	1.24***	1.18***	1.23***	1.18***
Married, spouse missing	1.13***	1.12***	1.12***	1.11***	1.12***	1.11***
Divorced	1.07**	1.07**	1.07**	1.07**	1.07**	1.07**
Widowed	1.32***	1.28***	1.33***	1.29***	1.33***	1.29***
Unmarried	1.01	1.02	1.02	1.02	1.02	1.02
Number of grandchildren	-	1.01**	-	1.01**	-	1.01**
Years of education	-	0.98***	-	0.98***	-	0.98***
Job tenure	-	1.01***	-	1.01***	-	1.01***
Health limitations	-	1.39***	-	1.39***	-	1.39***

*p<0.1; **p<.05; ***p<.01

For this sample, the probability of retirement is not larger for women than for men, when looking to social class. Apparently, retirement timing does not differ between men and women in Western Europe. However, this difference does exist if Europe as a whole is analyzed. Furthermore, when looking to social prestige and social status, there exists a small but significant difference in retirement probability (about 5 %).

The effect sizes for the restricted sample are slightly smaller in the restricted sample for most social classes. The same holds for social prestige and social status. This indicates that in Western Europe the difference in retirement timing associated with social position is smaller than in the rest of Europe. Also noteworthy is the difference in hazard ratios for white-collar workers in Model 1. In the restricted sample, no significant difference is found with semi- and non-skilled workers, while in the full sample the probability of retirement is 9 % lower.

For family situation, the estimated hazard ratios are very similar for the restricted extension sample and the whole sample. Therefore, differences in hazard ratios between the replication and extension sample are probably not due to the different number of countries analysed. It is more likely, that the difference in time-period has a larger effect. Also, the hazard ratios for the other control variables do not deviate much. In both samples, the presence of health limitations increases the probability of retirement with about 40 %.

5.2 Forced versus voluntary exit

5.2.1 Cause-specific hazard ratios for replication sample

Table 6 shows the estimates of the cause-specific hazard ratios for forced and voluntary exit. First, it can be noted that women run a lower risk of forced retirement (12 %) than men. Turning to social class, it appears that skilled manual workers are 22 % more likely to retire involuntarily earlier than semi- and non-skilled workers. Also, higher grade blue-collar and white-collar workers are more likely to be pushed from the labour market but the difference is not significant. All other classes run a lower risk of forced exit. Especially the petit bourgeois (56 %) and agricultural self-employed (39 %) run much lower risks of retirement due to ill health or unemployment. After controlling for number of grandchildren, years of education, job tenure and firm size, again workers in physically demanding jobs do retire significantly earlier. This is in line with earlier research (Blekesaune & Solem, 2005; Chirikos & Nestel, 1991).

Regarding voluntary retirement, females retire significantly earlier than males. Moreover, again a clear social gradient is found. The higher salariat, petit bourgeois and agricultural self-employed have a lower probability (more than 20%) of involuntary retirement than semi- and non-skilled workers. For the lower salariat and higher grade white-collar workers, there doesn't exist a significant difference. Higher grade blue-collar, lower grade white-collar and skilled manual workers are all about 20 % less likely to retire voluntarily than semi- and non-skilled workers.

Table 6: Hazard ratios of competing risk models of retirement timing (PCE model) for the replication sample

	Forced exit		Voluntary exit	
	Model 1	Model 2	Model 1	Model 2
Female	0.78***	0.86**	1.12**	1.21***
ESeC (ref: semi-and non-skilled)				
Higher salariat	0.71***	0.86	0.78***	0.76***
Lower salariat	0.83**	0.96	0.99	0.96
Higher grade white-collar	1.05	1.15	1.14	1.11
Petit bourgeois	0.44***	0.68**	0.59***	0.72***
Agricultural self-employed	0.61***	0.74	0.79***	0.82**
Higher grade blue-collar	1.17	1.26**	1.28***	1.22**
Lower grade white-collar	0.80*	0.90	1.19*	1.21**
Skilled manual	1.22**	1.27**	1.20**	1.15*
Family situation (ref: married, spouse employed)				
Married, spouse retired	1.85***	1.75***	1.92***	1.92***
Married, spouse homemaker	1.34***	1.28***	1.18**	1.16**
Married, spouse missing	1.15	1.11	1.36***	1.33***
Divorced	1.25*	1.27*	1.11	1.14
Widowed	1.27	1.22	1.31***	1.32***
Unmarried	1.33**	1.43***	1.05	1.05
Number of grandchildren	-	1.04***	-	1.00
Years of education	-	0.96***	-	0.98***
Job tenure	-	1.01***	-	1.01***
Firm size	-	1.19***	-	1.13***

*p<0.1; **p<.05; ***p<.01

Finally, as could be expected, the effects of family situation and the other control variables on the probability of retirement do not differ much between forced and voluntary exit. A noteworthy exception is found for unmarried respondents. They run a significantly higher risk of forced retirement (33 %) than married respondents of whom the spouse is employed. At the same time, the difference in timing of voluntary exit is not significant. This is probably related to differences in Social Security benefits for married and single individuals. Furthermore, Danø, Ejrnæs, and Husted (2005) found that health is an important determinant in the retirement decision of unmarried individuals. That is in line with the found results.

5.2.2 Comparison with Radl (2012)

The results of the cause-specific hazard estimates of Radl (2012) can be found in Table C1 in the Appendix. A first difference is found for the retirement timing of gender. When it comes to voluntary exit, in this research women were found to retire significantly earlier than men, while the difference that Radl (2012) found was not significant.

Also, for social classs, there are some deviations between the two estimates. For example, for higher grade white-collar workers no significant differences were found with semi- and non-skilled workers in the replication sample, although the probability of retirement was slightly higher. In contrast to this, Radl (2012) found that they retire significantly later if retirement is forced. Also for voluntary exit, the found hazard ratios were significant. Turning now to skilled manual workers, the reverse happens. Based on the replication analysis, it can be concluded that skilled manual workers have a more than 20 % higher probability of forced retirement, while Radl (2012) found that no significant difference exists.

For family situation, there also exist some differences in results. Married respondents of which the spouse is homemaker and unmarried respondents are found to have a significant higher probability of forced retirement, while Radl (2012) found no significant difference.

The number of deviations is somewhat larger for the cause-specific hazard models than for the full model. Part of this is caused by quite larger differences in the number of respondents that retired voluntary and forced. While Radl (2012) reported that 5,497 retirees stated as the reason for their retirement voluntarily and 2,030 forced, in the replication sample 4,921 reported voluntary and 2,622 forced. It is not clear what the cause is of this difference of almost 500 respondents. Furthermore, in the competing risks framework, respondents who experience the competing event are treated as censored. Therefore, the number of failures is much smaller. Hence, less information is available and deviations in variables will have a larger influence on the estimates. Finally, the deviations could again be due to the random component introduced by multiple imputation or a different implementation of the sampling weights.

5.2.3 Results for the extension sample

Table 7 displays the results of the competing risk framework for the models of social class for the extension sample. Females have a significantly lower probability of forced retirement than men in Model 1 (9 %). At the same time, their probability of retiring voluntarily is also significantly lower (about 30 %). This is in line with the earlier finding in the extension sample that females are more likely to retire early than men. It appears that most of this difference is due to voluntary exit.

Table 7: Hazard ratios of competing risks models for social class of retirement timing (PCE model) for the extension sample

	Forced		Voluntary	
	Model 1	Model 2	Model 1	Model 2
Female	1.09**	1.05	1.31***	1.27***
ESeC (ref: semi- and non-skilled)				
Higher salariat	0.60***	0.77***	0.76***	0.89***
Lower salariat	0.65***	0.78***	0.85***	0.95
Higher grade white-collar	0.78***	0.90	0.96	1.05
Petit bourgeois	0.47***	0.53***	0.57***	0.61***
Agricultural self-employed	0.57***	0.53***	0.67***	0.63***
Higher grade blue-collar	1.17	1.26	1.07	1.11
Lower grade white-collar	0.91*	1.00	0.91**	0.97
Skilled manual	0.93	0.90	1.01	0.97
Family situation (ref: married, spouse employed)				
Married, spouse retired	1.39***	1.34***	1.49***	1.45***
Married, spouse homemaker	1.31***	1.21**	1.40***	1.32***
Married, spouse missing	1.10*	1.09*	1.13***	1.13***
Divorced	1.13**	1.16***	0.96	0.99
Widowed	1.38***	1.31***	1.30***	1.25***
Unmarried	1.16**	1.21***	0.97	1.00
Number of grandchildren	-	1.04***	-	1.03***
Years of education	-	0.95***	-	0.97***
Job tenure	-	1.01***	-	1.01***

*p<0.1; **p<.05; ***p<.01

Higher grade white-collar workers are the only workers that retire earlier than semi- and non-skilled workers, both voluntarily and forced, although the difference is not significant. Also, for lower grade white-collar workers and skilled manual workers, the difference between forced and voluntary retirement timing is small, relative to semi- and non-skilled workers. In all four models, the petit bourgeois and agricultural self-employed are again amongst those who retire latest. For the higher and lower salariat, higher grade white-collar, petit bourgeois and agricultural self-employed, the probability of forced retirement is smaller than the probability of voluntary retirement, relative to semi- and non-skilled workers.

Table 8 shows the estimated hazard ratios of the cause-specific models for social prestige and social status. Note that the parameters for SIOPS and ISEI are estimated separately, but reported in one table. Furthermore, the hazard ratios for gender, family situation and the other control variables can be found in Table D1 in the Appendix, because they are very similar to the estimated hazard ratios of the social class models in Table 7.

Again, no significant difference is found between those with a low and moderate position. Workers with an average or high position retire significantly later, but the difference becomes smaller when retirement is voluntary. Especially those in high positions have a low probability of forced retirement (42 % less). Turning to status, a similar pattern is found. Those with a higher status retire later, especially when it comes to forced retirement. However, for voluntary retirement, there is no significant difference found between low, moderate and average status. Only those with high status have a 16 % smaller probability of voluntary retirement. After controlling for number of grandchildren, years of education and job tenure the difference between low and high status for voluntary retirement is no longer significant.

Table 8: Selected results of the competing risks models of retirement timing (PCE model) for social prestige and social status for the extension sample

	Forced		Voluntary	
	Model 1	Model 2	Model 1	Model 2
SIOPS (ref: low prestige)				
Moderate prestige	0.97	0.99	1.01	1.01
Average prestige	0.76***	0.87**	0.92**	0.99
High prestige	0.58***	0.74***	0.72***	0.82***
ISEI (ref: low status)				
Moderate status	0.93	0.99	0.99	1.03
Average status	0.79***	0.91	1.00	1.09***
High status	0.64***	0.82***	0.84***	0.99

*p<0.1; **p<.05; ***p<.01

Note: separate models have been estimated for social position and social status.

5.2.4 Comparison between samples

When comparing the hazard ratios of the competing risk framework for the replication sample and the extension sample, the first thing that stands out are the hazard ratios for gender. In the replication sample, females are significantly less likely to retire forced than men, while in the extension sample they are significantly more likely. This difference probably is again due to the difference in countries analysed, as discussed in Section 5.1.5.

Higher grade white-collar workers from the extension sample have a 22 % lower probability of forced retirement in Model 1. However, in the replication sample this was found to be 5 % higher, although that effect was not significant. Moreover, higher grade blue-collar workers were found to retire significantly earlier voluntarily (about 25 %), while in the extension sample the difference is smaller (about 10 %) and not significant. Another difference can be found for skilled manual workers. In the extension sample, no significant difference was found with semi- and non-skilled workers. At the same time, they were found to retire about 20 % later in the replication sample, both forced and voluntarily.

Turning now to family situation, again the probability of retirement, both forced and voluntary, of married respondents from whom the spouse is retired is in the extension about half of the probability in the replication sample. For widowed respondents, the hazard ratios are relatively similar for forced exit (about 30 %), but in the extension sample, the difference is significant, while in the replication sample it is not.

6 Conclusion

This research has considered the relationship between socio-economic position and the timing of retirement and the extent to which retirement is voluntary or forced. Using data of SHARE wave 1, first, the work of Radl (2012) has been replicated. Next, his work has been extended by using a more recent sample of SHARE respondents. Furthermore, a broader definition of social position was used that did not only take into account the effects of social class but also of social prestige and social status. A piecewise-constant exponential model has been used to model the retirement decision, and to estimate cause-specific hazard models for voluntary and forced exit.

The results showed that there exists a clear social gradient in work exit. The timing of and reason for retirement vary by class. The petit bourgeois and agricultural self-employed are the ones who retire latest. At the same time, members of the higher grade blue-collar, skilled manual and semi-and non-skilled class often retire early. Those classes also run a higher risk of involuntary employed.

Also, social prestige and social status influence the retirement decision. Workers in occupations with a higher prestige tend to retire significantly later, and more often voluntarily. When it comes to social status, I conclude that the probability of forced retirement is smaller for those in occupations with higher status. Nevertheless, it does not mean that they retire later. Finally, it can be concluded that the different measures of social position (ESeC, ISEI and SIOPS) to a large extent overlap. However, they are conceptually different and their interpretation is not similar. Therefore, it is worthwhile to consider multiple indicators when investigating the effect of social position.

Another interesting finding is that in Western Europe socio-economic position seems to influence retirement timing to a smaller degree then in the rest of Europe. Furthermore, it has been found that women retire significantly earlier than men and also marital status and employment status of the partner have are related to retirement timing. Individuals of which the spouse is already retired are found to retire much earlier.

It should be noted that for the extension sample, 20 % of retirees missed information on the reason for retirement. Those observations have been excluded from the competing risks analysis. Therefore, the results of the cause-specific hazard models should be interpreted with caution. I have tried to model this sample selection using the estimator proposed by F. J. Boehmke, Morey, and Shannon (2006) with the Stata package dursel (F. Boehmke, 2005). However, no convergence could be achieved for the maximum likelihood estimator, probably due to a lack of explanatory power for the selection equation. Moreover, this estimator is not suitable for survey data with time-varying covariates. Therefore, future research could aim at developing a model to correct for sample selection for these types of models.

Another limitation of this research is that due to data limitations, the variable firm size could not be used in the analyses for the extension sample. I have estimated the model including firm size for the subset of the sample which was not missing that variable (20 % of respondents). However, the results deviate a lot at certain points, especially for the variables for social prestige and social status. Therefore, I have chosen to omit this variable from the analysis for the replication sample.

What also should be noted with respect to this research is that occupations and social position are not always comparable between countries (Elias, 1997). Converting occupations to ISCO codes is an inexact process. Interpretation and application of conversion schemes can differ by countries, and therefore can produce unreliable results.

Nevertheless, it is clear from this research that retirement timing and the availability of pathways towards retirement are related to socio-economic position. This suggests a number of policy implementations. Extra care should be given to workers in physically demanding jobs, like semi- and non-skilled, skilled manual and lower grade blue-collar workers, because they often retire involuntarily due to health problems or unemployment.

7 References

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A Sample selection

Table A1: Sample selection for replication and extension sample

	Replication sample	Extension sample
Total	30,424	76,520
Respondents in Israel	-2,449	-2,132
Born before 1930	-5,105	-20,519
Born after 1949	-5,973	-5,053
Subtotal	16,897	48,816
Homemaker	-2,697	-3,069
Homemaker ISCO code	-25	-
Never worked	-83	-143
Employment status Other	-243	-632
Subtotal	13,849	44,972
Missing retirement year	-282	-1,809
Retired before 50	-1,290	-2,865
Missing reason for retirement	-60	-
Missing sample weight	-9	-
First wave is wave 7	-	-8,369
Final sample	12,208	31,929

B Multiple imputation

Multiple imputation can be used to fill in missing values when values are missing at random [4]. This means that the probability that a value is missing depends on other variables, but only on observed data. The advantage of using chained equations for multiple imputation is that each variable can be modelled using their own distribution. The process consists of five steps:

Step 1: Each variable with missing values is imputed using mean imputation. That is, all missing values are set equal to the mean of that observation.

Step 2: The mean imputations for one of the variables are set back to missing. This variable is regressed on all other variables in the imputation model.

Step 3: Predictions are obtained from the regression model and used to predict the missing values.

Step 4: Step 2 and 3 are repeated for all variables. Such that at the end of one cycle, all missing values have been filled in.

Step 5: Step 2 till 4 are repeated and imputations are updated after each cycle. After a fixed number of cycles, the burn-in period, the imputations are saved as the first imputation set.

For the multiple imputation, 5 imputation sets are used and the burn-in period is set to 20 cycles to ensure convergence. For the replication part, the following variables are imputed: ESeC class, years of education, firm size and job tenure at the age of 50. For ESeC a multinomial logit specification is used, for firm size an ordered logit specification and for job tenure and years of education, predictive mean matching is used. For this last method, the ten nearest neighbours are used, as suggested by Morris, White, and Royston (2014) Moreover, country of residence, gender and family situation at the age of 50 are used as extra predictors. Furthermore, following I. R. White and Royston (2009), also the survival time in years and the Nelson-Aalen estimator of the cumulative hazard rate function are used as predictors.

In the extension part, the variables ESeC class, SIOPS class, ISEI class, average number of grandchildren, years of education and job tenure at the age of 50 are used. As extra predictors, again the survival time in years and the Nelson-Aalen estimator are used. Furthermore, family situation at the age of 50, gender, country of residence, one digit ISCO-codes, health limitations at the age of 50, self-reported general health at the age of 50, International Standard Classification of Education (ISCED) codes as classification of education level and the number of children are

[4] This section is based on Azur, Stuart, Frangakis, and Leaf (2011). Interested readers are referred to Van Buuren (2018) for more details on multiple imputation using chained equation.

used. As model specifications, a multinomial logit model is used for ESeC, both SIOPS and ISEI use ordinary least squares estimation, years of education is based on an ordered logit model, while the other variables use predictive mean matching based on the ten nearest neighbours. As the variable ESeC class has some relatively small classes, there were some problems with convergence. Therefore, the predictors country of residence and education level have been omitted for this variable.

C Results competing risks framework replication sample

Table C1: Hazard ratios of competing risk models of retirement timing (PCE model) for the replication sample

	Replication				Radl (2013)			
	Forced exit		Voluntary exit		Forced exit		Voluntary exit	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Female	0.78***	0.86**	1.12**	1.21***	0.88**	0.88*	1.04	1.12
ESeC (ref: semi-and non-skilled)								
Higher salariat	0.71***	0.86	0.78***	0.76***	0.49***	0.66***	0.85	0.78**
Lower salariat	0.83**	0.96	0.99	0.96	0.60***	0.76***	1.14	1.04
Higher grade white collar	1.05	1.15	1.14	1.11	0.70***	0.81**	1.31*	1.23**
Petit bourgeois	0.44***	0.68**	0.59***	0.72***	0.45***	0.51***	0.63***	0.56***
Agricultural self-employed	0.61***	0.74	0.79***	0.82**	0.62***	0.58***	0.76**	0.56***
Higher grade blue collar	1.17	1.26**	1.28***	1.22**	0.90	1.01	1.47***	1.28***
Lower grade white collar	0.80*	0.90	1.19*	1.21**	0.89*	0.99	1.18***	1.19***
Skilled manual	1.22**	1.27**	1.20**	1.15*	1.11	1.16	1.26***	1.16**
Family situation (ref: married, spouse employed)								
Married, spouse retired	1.85***	1.75***	1.92***	1.92***	1.60***	1.53***	1.91***	1.90***
Married, spouse homemaker	1.34***	1.28***	1.18**	1.16**	1.05	0.99	1.24***	1.18*
Married, spouse missing	1.15	1.11	1.36***	1.33***	1.11*	1.10	1.29***	1.25***
Divorced	1.25*	1.27*	1.11	1.14	1.32	1.36	1.11**	1.21***
Widowed	1.27	1.22	1.31***	1.32***	1.29	1.21	1.27***	1.31***
Unmarried	1.33**	1.43***	1.05	1.05	1.09	1.09	1.16***	1.14***
Number of grandchildren	-	1.04***	-	1.00	-	1.05***	-	1.00
Years of education	-	0.96***	-	0.98***	-	0.95***	-	0.98***
Job tenure	-	1.01***	-	1.01***	-	1.01***	-	1.03***
Firm size	-	1.19***	-	1.13***	-	1.00	-	1.00***

D Results competing risks framework extension sample

Table D1: Hazard ratios of competing risk models of retirement timing (PCE model) for social prestige and social status for the extension sample

	Forced				Voluntary			
	Social prestige		Social status		Social prestige		Social status	
	Model 3	Model 4	Model 5	Model 6	Model 3	Model 4	Model 5	Model 6
Female	1.09**	1.07**	1.10***	1.09**	1.32***	1.30***	1.32***	1.29***
SIOPS (ref: low position)								
Moderate position	0.97	0.99	-	-	1.01	1.01	-	-
Average position	0.76***	0.87**	-	-	0.92**	0.99	-	-
High position	0.58***	0.74***	-	-	0.72***	0.82***	-	-
ISEI (ref: low status)								
Moderate status	-	-	0.93	0.99	-	-	0.99	1.03
Average status	-	-	0.79***	0.91	-	-	1.00	1.09***
High status	-	-	0.64***	0.82***	-	-	0.84***	0.99
Family situation (ref: married, spouse employed)								
Married, spouse retired	1.41***	1.35***	1.40***	1.35***	1.51***	1.46***	1.51***	1.47***
Married, spouse homemaker	1.31***	1.21**	1.29***	1.20**	1.39***	1.30***	1.38***	1.30***
Married, spouse missing	1.09*	1.09*	1.09*	1.08*	1.13***	1.12***	1.13***	1.12***
Divorced	1.13**	1.17***	1.13**	1.17***	0.96	0.99	0.96	1.00
Widowed	1.39***	1.32***	1.38***	1.32***	1.30***	1.26***	1.31***	1.26***
Unmarried	1.16**	1.21***	1.17**	1.21***	0.97	1.00	0.97	1.00
Number of grandchildren	-	1.04***	-	1.03***	-	1.03***	-	1.03***
Years of education	-	0.95***	-	0.95***	-	0.98***	-	0.97***
Job tenure	-	1.01***	-	1.01***	-	1.01***	-	1.01***

E Programming code

The programming code used in this research is provided in the supplementary files. It contains all code necessary to replicate the results, and consist of the following files:

1. Stata code
   (a) Replication_code: Code for replication analysis of the work of Radl (2012)
   (b) Extension_code: Code for the extension analysis
2. Matlab code
   (a) Isco88toEsec: Code for converting ISCO-88 to ESeC
   (b) Isco08toEsec: Code for converting ISCO-08 to ESeC
   (c) Iscco08toIsei: Code for converting ISCO-08 to ISEI
   (d) Isco08toSiops: Code for converting ISCO-08 to SIOPS