Retirement Age Trap: RDD Approach to Terminated Retirement Spells

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Abstract

Regression discontinuity (RD) analysis of retirement durations and retiree death ages is conducted with the Finnish year 1947 birth cohort. Data consist of observations from the sample follow-up period in 1.1.2007 – 31.12.2019. For the year 1947 cohort the eligible retirement age with old-age pension is between the ages of 63 and 68 years. However, the observed pension ages are quite often less than 63 years although the statutory minimum retirement age regulates persons' retirement times. This means that for some retirees age of 63 years constitutes a queuing age that is against their retirement intentions, and this affects their retirement spells. We find with RD methods that *close after death* age of 63 years, the retirement spells discontinuously *shortens* although the higher death age should give room for the longer retirement spells. The point estimates for regression discontinuity effects on terminated retirement spells are in the range of from –1.09 to –0.56 in loss of year depending on the used sub-samples, covariates, and estimation methods. These findings are interpreted to conflict retirement intentions of retirees retiring at age of 63 years.

Keywords. Regression discontinuity, retirement duration, age of death, statutory minimum retirement age
JEL Codes: J26, J10, C21

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1. Introduction

In the dynamic life-cycle models focusing on retirement, the representative agent takes *expected lifetime* or some related estimate of it as a given parameter in his/her "optimal" retirement date decision (see e.g., Bloom et al., 2004; Kalemli-Ozcan and Weil, 2010). The exact retirement time or age is quite seldom explicitly solved in the literature that gives different comparative static results with respect to retirement age. The papers on how expected survival time or time of death determine retirement timing are almost non-existing. This is understandable as the retiree faces the following relation when planning his/her length of retirement period

$$retD^{I} = AGE_{D}^{*} - retT > 0 \qquad (1)$$

where $retD^{I}$ is the intended or the planned retirement spell or duration, AGE_{D}^{*} is an estimate of the age of death, and *retT* is the chosen retirement age. The importance of this equation must be stressed as we can argue that the person in the first place try to maximize his/her (expected) retirement duration and pension level sustained by the lifetime labour supply, and the retirement age is subordinate to this target. However, the above retirement spell calculation is a hard problem at the individual level because valuation mistakes and forecast biases on the age of death estimate are typically large. This means that retiree's estimate of his/her remaining lifetime can differ greatly from his/her actual lifetime. Note that whatever is the person's estimate for his/her life length it also affects his/her intended retirement age, i.e., the chosen retirement age is not independent of estimate of survival time.

We try not to solve the evident stochastic maximization problem buried in the Eq. 1). Instead, we focus next on the relevant empirical literature in this context. Albeit the individuals can often determine their retirement entry within the eligible age limits, retirement decisions are influenced by factors over which individuals have no or little control such as institutional regulations, employment status or health (Coppola and Wilke, 2014). However, the main result here is that retirement expectations are quite accurate regarding the actual retirement age (e.g., Chan and Stevens, 2008; Benitez-Silva and Dwyer, 2005; Cobb-Clark and Stillman, 2009). Part of this literature focus on changes in pension and statutory retirement ages showing that expectations are quite sensitive to changes in the institutional framework but there exists heterogeneity in the adjustment of expectations (for more details, see Coppola and Wilke, 2014).[1)]

Some empirical papers have linked subjective survival estimates to retirement decisions. The results so far are quite mixed. Hurd et al. (2004) report that those with particularly low expectations of survival to age of 85 are more likely to retire earlier. Delavande et al. (2006) find no impact of subjective survival on the retirement probability over the subsequent two years for those not retired at age of 62 years. However, O'Donnell et al. 2008) show with data from the UK that individuals that are extremely pessimistic about their chances of survival are least likely to retire. For more positive expectations they find that after initially rising steeply the propensity to retire falls as survival expectations improve. When controlling for health, there is still a substantial and significant effect of survival expectations on retirement age.

van Solinge and Henkens (2009) focus on subjective life expectations, retirement *intentions*, and actual retirement times with Dutch retirement data in two waves from years 2001 and 2007. They show that employees who expect to live longer, intend to retire later than those who expect a shorter life span. However, on average, older employees retired 1.6 years earlier than originally intended. The results suggest that particularly employees with a high perceived life expectancy and an intention to work longer don't succeed in carrying their intentions into effect. Khan et al. (2014) focuses also on the actual retirement age and on the planned retirement age with the US data. They find that respondents who are more optimistic about their survival to age 75 or 85 years also expect to work five months longer on average, and the actual retirement behaviour increases also with subjective life expectancy.

With the results above in background we analyse observed retirement durations among the retirees with the Finnish year 1947 birth cohort. In analysis we use regression discontinuity designs (RDD) methods. We propose the following research question "Has the death happening after retirement around the minimum eligible old age retirement age of 63 years an effect on the length of retirement spell". We elucidate with a reduced approach that actual retirement durations for some retirees must be far from what they have planned. We find that close to age

[1)] Gustafsson (2023) proposes that another form of incomplete information, i.e. pension illiteracy, has effects on life time labour supply and retirement.

of *death after* 63 years the retirement durations discontinuously *shortens* although the higher death age should allow for the longer retirement durations.

The remainder of the paper is organized as follows. Our data and conceptual framework are introduced in Section 2. Section 3 focuses on RDD methods and gives our main graphical results. Section 4 provides RD regression model estimation results. Finally, Section 5 concludes.

2. Why is the minimum eligible old-age retirement age harmful for some person?

2.1. Data

Our data consists of sub-sample (58.165 persons) of the year 1947 birth cohort in Finland (108.168 persons) during the sample follow-up period of 1.1.2007 – 31.12.2019. Our focus is on the length of observed retirement durations when retirement has happened after the age of 59 years. For the year 1947 birth cohort the eligible old-age pension age window is between ages of 63 and 68 years but quite many persons retire before age of 63 years for different reasons (for more details on data, see Appendix 1). As our data consists of retirement and death ages at birthday precision, we can do RD analysis very close to cut-off age of 63 years.

2.2. Discontinuity at age of 63 years

We argue that the lowest eligible old-age pension age of 63 years constitutes an important cut-off age with respect to observed retirement durations. Our "causal story" here is the argument that if the persons have low expectations on the lengths of their remaining lifetimes, they try to retire early as possible, i.e., earlier than persons with high survival expectations. More precisely, we argue that persons with low subjective or objective life expectations face the "gate" of the lowest eligible old-pension age of 63 years too distant for them. They can and try to avoid it with alternative pensions arrangements before age of 63 years, e.g., they apply for and are allowed for disability, unemployment, part-time, and early retirement pensions that end by moving to permanent old-age pension (see Appendix 1, Tables 1B-1C). Note that old age pension before age of 63 years also concerns some special job statuses like firemen, military and cost-guard officers, and persons having special individual elderly pension contracts (e.g., golden handshakes). All in together this means that many persons retiree before age of 63 years but for many this age constitutes a statutory waiting or queuing age that is against their retirement intentions and is not optimal for them.

In this context this means that for a given (low) retirement age, a high death age means a long retirement spell. Now, the death age – here taking place only after retirement – plays an important role in the analysis. We propose a novel RD model where death age acts as a running variable and the length of terminated retirement duration is the main outcome variable of interest. Death age is a valid running variable as it is typically random and it can't be easily manipulated by the RDD units, i.e., retirees. This also connects our RD model close to method of randomly controlled trials (RCT).

3. RDD with retirement spells

3.1. Regression discontinuity designs

Regression discontinuity designs (RDD) have obtained large interest in economics along with the "credible revolution" in econometrics. With the latter we mean the different methods employed in the treatment effect literature trying to elucidate "causal effects" in the data mimicking the results of the RCT's in medical and natural sciences. Typical RD studies in economics have focused on the effects of educational achievement on later educational enrolments and career earnings, labour market program and policy effects on labour supply, and age depend care effects on health levels and care utilization (see e.g., Lee and Lemieux, 2010). At this moment advances in statistical foundations of RD methods have lifted the analysis to new levels with robust testing approaches and solid methodological framework (see e.g., Cattaneo et al., 2020c).

3.2. Discontinuity of outcome at treatment rule

Age or time is quite natural assignment or *running variable* X that determines treatment by turning some policy or rule on at some specific age or time, say $D=1$ when $X \geq c$. Now after age c the person belongs to the treatment group and before age of c he/she belongs to the control group, i.e. $D=0$ when $X < c$. Note that at the threshold or at the cut-off age c nothing happens to this running variable X per se – it is still a continuous function around this age. Instead, the *outcome variable* Y under study may respond discontinuously to the treatment turning on at the cut-off age c.

In technical terms we have a treatment effect $\theta(x) = E[\theta \mid X = x]$, and we are interested in estimate of $\theta(x) = m_{D=0}(x) - m_{D=1}(x)$ where

$$m_{D=0}(x) = E[Y_0 \mid X = x] \text{ and } m_{D=1}(x) = E[Y_1 \mid X = x]. \qquad (2)$$

At the cut-off c we set that $m(c^+) = \lim_{x \downarrow c} m(x)$ and $m(c^-) = \lim_{x \uparrow c} m(x)$. Hahn et al. (2001) propose the following core *identification theorem* for RDD (see also Hansen 2021, Chapter 21).

> Assume that treatment is assigned as $D = \mathbf{1}\{X \geq c\}$. Suppose that $m_{D=0}(x)$ and $m_{D=1}(x)$ are *continuous* at $x = c$. Then $\overline{\theta} = m(c^+) - m(c^-)$.

The continuity assumption has a high importance here and it means that the conditional expectations functions (*CEF*) for untreated and treated outcomes of *Y*, $m_{D=0}(x)$ and $m_{D=1}(x)$, are continuously affected by the running variable *X*. Thus, at the treatment cut-off, RD identifies the possible conditional local average treatment effect (LATE) as a limit result of endpoints of CEF's. The rationale behind this comparison is that treated and control units in a *small* neighbourhood or window around the cut-off are comparable in the sense of having similar observed and unobserved characteristics, i.e., units' characteristics do not change at the cutoff. The only remaining difference between units will be their treatment status, at least in terms of their potential outcome mean regression functions (Cattaneo et al. 2020b; 2020c, Section 2).

In practice this means that CEF's $m_{D=0}(x)$ and $m_{D=1}(x)$ are continuous at the cut-off and the density of *X* must be also continuous at $x = c$. This is the *non-manipulation assumption* of RD model that is violated if the density of running variable *X* is discontinuous around $x = c$ (or elsewhere) indicating that *X* is not independent in the presented RDD, e.g., it is manipulated by the design units. Nice thing here is that this assumption is easily tested. More demanding task is to estimate the treatment effect $\overline{\theta} = m(c^+) - m(c^-)$ effectively and unbiased under the *continuity* of $m_{D=0}(x)$ and $m_{D=1}(x)$. Typically, linear OLS method is seldom suitable to support the approximate correct regression functions as estimates for CEF's.

3.3. Death age as the running variable

To motive our RD model approach, we produce following Figure 1. Graphical methods are useful in the RDD context to show how cut-off point on the running variable is related to the possible outcome variable discontinuity. The potential discontinuity is estimated with binned data (N_{EFF} = effective sample sizes on both sides of cut-off point), i.e., sample averages of nearby observations (x,y) –pairs, and with "optimal" order polynomial fits at both sides of cut-off point (see Calonico et al. 2017).

In the Figure 1. the running variable is the *age of retiree*, and the retirement duration is the outcome variable. We see a discontinuity in retirement durations at the cut-off age of 63 years and the length of durations *jump down* in average at the cut-off age. Note that the values of *AGE* variable in Figure 1. refer to the *death ages* up-till age of 73 years during the sample follow-up time, and to the ages of still *alive* persons with age above of 73 years at the end of follow-up. This means that cut-off age of 63 years refers to the death age.

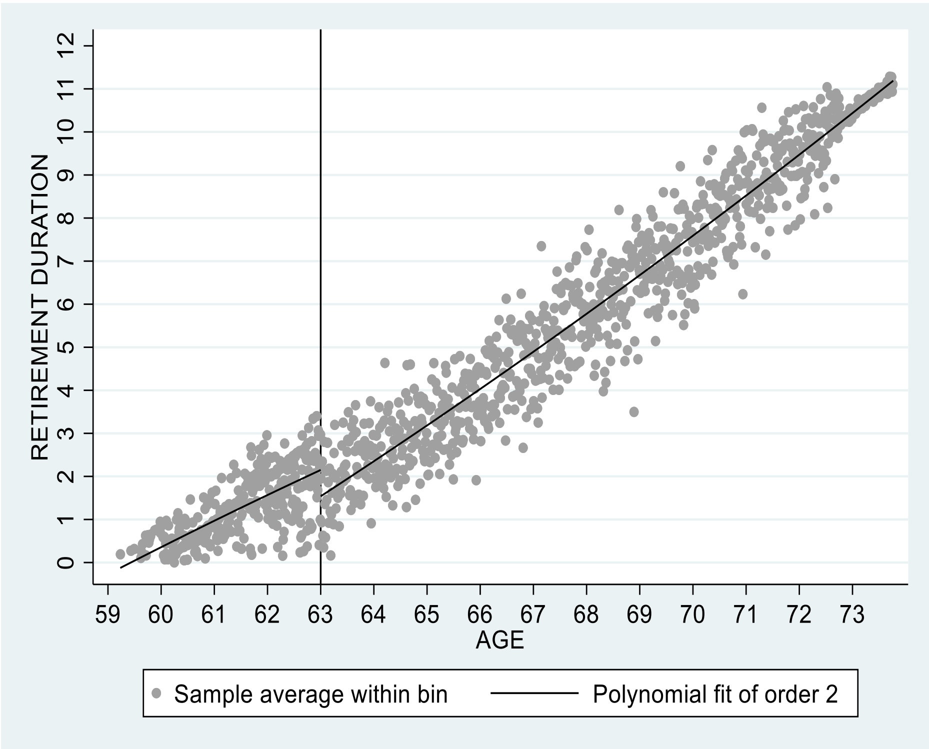

Figure 1. Regression discontinuity at age of 63 years in retirement durations with (death) age as running variables (N = 58615)

Figure 1. shows that durations shorten *close after the death age* of 63 years compared to death age close before it. How is this possible? In the following we try to understand this interesting and novel result in details. Before the retirement duration RD model estimation for point effects, we check that the death age is continuous variable especially around the eligible minimum age of old age pensions of 63 years. In other words, Figure 1. result is not an outcome of density discontinuities in death ages at the cut-off age of 63 years.

3.4. Testing for density discontinuity in death ages

In a local neighbourhood near the cut-off age, if the number of observations below the cut-off is surprisingly different from the number of observations above it, then the underlying assumption of absence of precise manipulation of running variable is violated. If not violated, random change would place roughly the same amounts of units on either side of the cut-off, leading to a continuous probability density function at the treatment cut-off point (see Catteneo et al., 2018; Catteneo et al., 2020c). Figure 2. depicts the robust local polynomial density estimates of retiree death ages at both sides of cut-off age 63 years between death ages of 59 and 68 years with 95% CI's. Appendix 2 gives sub-sample results with alternative death age windows and local bandwidths (BW's) approaching the eligible minimum old-age pension age. Irrespectively of used death age window or BW's our density estimates show that the continuity assumption is valid for our running variable.

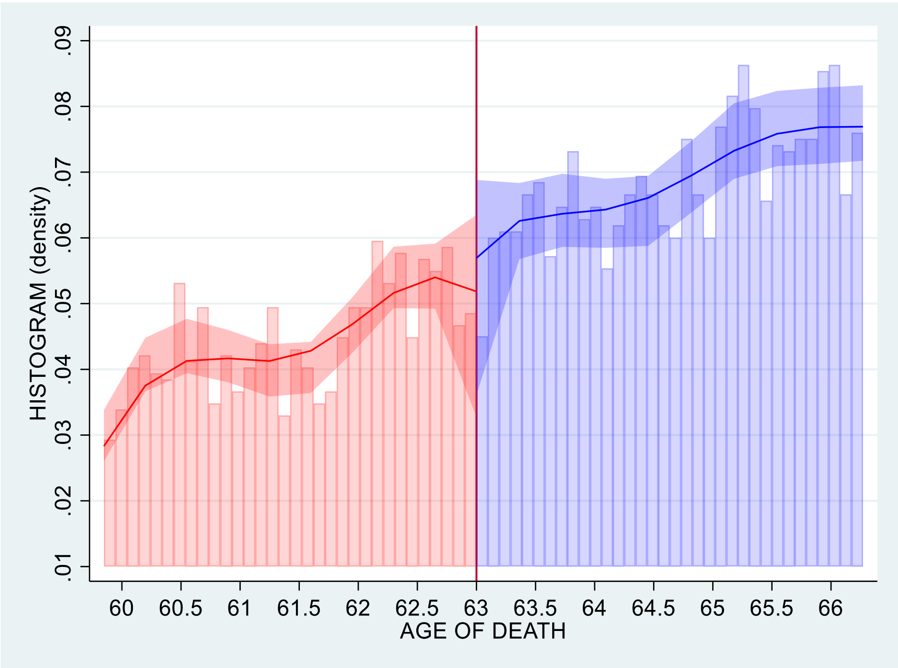

Figure 2. Estimated density and histogram of death ages with cut-off death age of 63 years.

Table 1. gives more formal test results for smoothness of death age densities around cut-off age of 63 years (see also, Appendix 2, Table 2A). The test is a robust approach based on the minimization *MSE* –criterion for local polynomial density estimate with respect to BW choices close to the cut-off (see Catteneo et al., 2018). The test balances optimally the trade-off between precision (variance) and bias of estimates with corrections for higher order approximations.

All test results show that the null hypothesis – density of the running variable is continuous at the cut-off – is not rejected. In general terms, the obtained continuity results in the death age variable are expected because we can't assume that persons can manipulate their (random) death ages, i.e., deaths happen with equal probabilities very close to cut-off age of 63 years. In other words, death treats persons independently (i.e., randomly) of other factors at the close margin of cut-off age. Next question is how this random death age assignment affects the length of terminated retirement spells and other variables that are related to retirement age decisions.

Table 1. RD manipulation test using local polynomial density estimation.

Running variable: ALL DEATH AGES (retT > 59)

N = 6438, N_{EFF} = 347 and 569, BW_{OPT} = -1.48,1.48)

Method	T	p-value >|T|
Robust	0.7979	0.4249

P-values of binomial tests. (H0: prob = 0.5)

Window Length/2	<cut-off	=>cut-off	p-value >|T|
0.042	9	11	0.8238
0.084	22	23	1.0000
0.126	36	41	0.6488
0.168	44	61	0.1180
0.211	56	73	0.1587
0.253	68	92	0.0687
0.295	83	108	0.0822
0.337	95	118	0.1315
0.379	108	134	0.1078
0.421	118	148	0.0752

3.5. Is it retirement age or death age that determines retirement durations?

At the deeper level the above discontinuity results in Figure 1 can be understood with (ex-post) retirement duration counting equation corresponding to Eq. 1) above

$$retD = AGE_D - retT \geq 0 \qquad (3)$$

where *retD* = observed retirement duration, AGE_D = observed death age, and *retT* = observed retirement age. The equation shows clearly, with the given value of retirement age *retT*, the higher death age means longer retirement duration *retD*. However, we saw in Figure 1. that this not happens around the death age of 63 years. Why we see a break downwards in the smooth increasing relation between death age and retirement duration at the minimum eligible age for old-age pension?

Here's some answers in terms of summary statistics. Although AGE_D is a random event – also at age of 63 years as shown above – and *retT* depends on persons' retirement intentions and plans, retirement takes place nevertheless very often at the minimum eligible old-age retirement. This means that large amount of retirement "packs" close to the age of 63 years making the sample average of retirement durations short with death ages close after age of 63 years. The counter argument to this is that the number dying retirees should be also large at age of 63 years because large number of persons are retiring at this age. This can be true, but here the things are different. Now, with reference to above counting equation and persons retirement behaviour, the number of *retT*'s is proportional *larger* than the number of (random) AGE_D's is close after age of 63 years, and this makes the values of *retD*'s small (see Appendix 3).

Some additional local RD plots with retirement durations, retirement ages, and *death ages* between ages of 59 and 68 years are illuminating here. We use first retirement age *retT* as

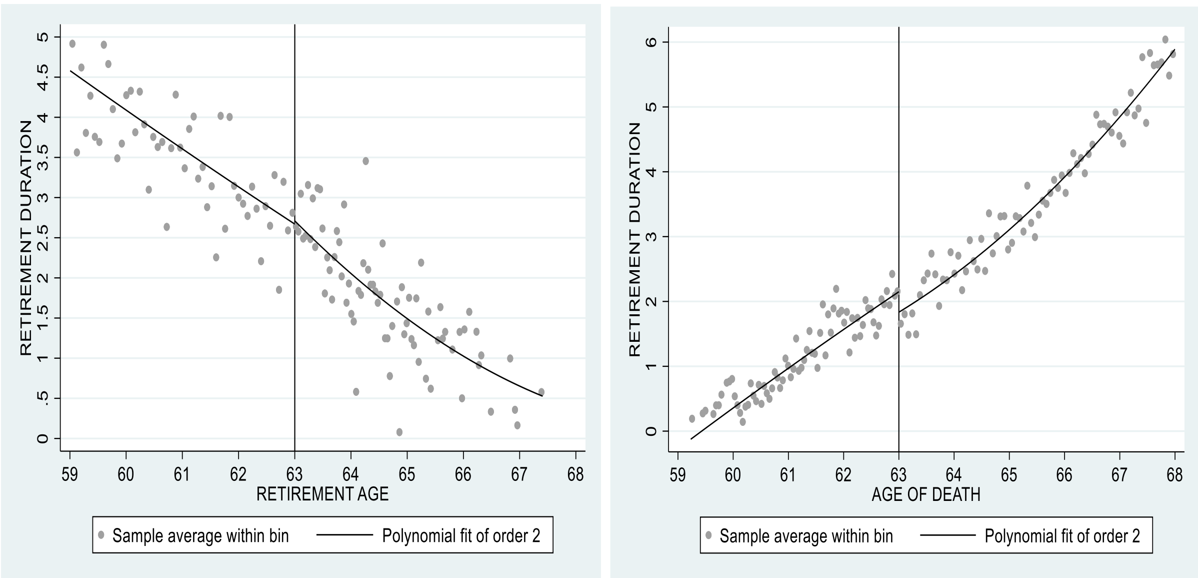

Figure 3. Regression discontinuities in retirement durations with retirement age (59 < *retT* < 68) and death age (59 < AGE_D < 68) as running variable (N = 2900).

running variable with retirement duration *retD* as the outcome variable. Note here the diffe-rence in sample size with Figure 1. above where the whole sample was used. Figure 3. (left panel) shows clearly that there is no RD effect on retirement durations happening at *retirement age* of 63 years. Only very small kink in the regression function is detected at that age. In the right panel *death age* is the running variable. Retirement durations jump down once again discontinously at the death age of 63 years. The graphs in Figure 3. show, that persons, who died close *before* the minimum retirement age of 63 years, have retired earlier than those who died close *after* with the age of 63 year. Alternatively, in terms of Eq. 3), at the death age of 63 years, longer durations can happen only if retirement ages are lower.

All this means – quite trivially – that when death ages, that are almost uniformly distributed close to age of 63 years, are scaled with quite differently distributed retirement ages, a jump downward in terminated retirement durations close after death age of 63 years is observed. In other words, our novel result indicates that retirees planned or “forced” to retire at age of 63 years – and unfortunately die close to this age – have shorter retirement spells compared to those retired somewhat earlier.

Following Table 2. gives means of death ages, retirement durations, and retirement ages for persons at both sides of the cut-off death age of 63 years. Rows in Table 2 focus on values above and below the cut-off age. In the first two rows, death ages and retirement durations are quite different but there is close to 10 month difference in retirement ages (61.63 – 60.32). Those who die after age of 63 years retire later if they retire before age of 63 years.

Table 2. Means of death ages, retirement durations, and retirement ages at the cut-off value of 63 years (SE of means in parethesis).

DEATH and RETIREMENT AGES	AGE_D	retD	retT
AGE_D < 63 and retT < 63, N = 569	61.70 (0.04)	1.38 (0.04)	**60.32** (0.03)
AGE_D ≥ 63 and retT < 63, N = 5025	68.59 (0.04)	6.96 (0.05)	**61.63** (0.02)
62.5 < AGE_D < 63 and retT < 63, N = 143	62.74 (0.01)	**1.94** (0.08)	**60.80** (0.08)
63 ≤ AGE_D < 63.5 and retT < 63.5, N = 191	63.27 (0.01)	**1.67** (0.10)	**61.40** (0.09)

When death age window is set close to cut-off age of 63 years (62.5 - 63.5, rows 3-4), retirement age difference is smaller (circa 6 months), but now the retirement duration is longer for those who die close before age of 63 years compared to ones who die close after this age. This replicates of our main results but now we see that retirement (age) behaviour differs among the person dying close to age of 63 years.

4. RD treatment effect estimates on retirement spells

4.1. Effect estimates

Next, we use Calonico et al. (2017) robust nonparametric local polynomial method (R/Stata: **`rdrobust`**) to estimate the treatment effect with the above RD design. RD effect estimation is based on MSE_{MIN} –optimal bandwidth selection approach with respect to bias-variance trade-off problem in regression smoothing estimation. Note that (global) linear parametric OLS approach to estimation of treatment effect is in most RDD applications biased or not even suitable due the possible non-linearity of CEF’s around the cut-off. The robust methods correct and adjust for estimation and inference biases in optimal way with respect to approximation errors in the derivatives of local polynomial fits (see Cattaneo et al. 2020c, Section 4).

We estimate with **`rdrobust`** – module for the treatment effect at the cut-off death age of 63 years with different death age windows. In Table 3. we observe that the RD_{ROBUST} estimate is –0.957 when we use the full sample. In other words, above the cut-off death age, the average (local) retirement duration is 0.96 years *less* than it is below the cut-off age. Precisely, those who survive *close to above* the age of 63 years have (in average) 11 months shorter retirement durations than those who survive *close below* age of 63 years. When running variable contains only the death persons with ages than less 68 years RD_{ROBUST} estimates are close to above full sample result. With window of 61 – 65 death ages, the effect estimates is – 0.822.

TABLE 3. RD_{ROBUST} EFFECTS ESTIMATION RESULTS WITH DIFFERENT DEATH AGE WINDOWS

OUTCOME VARIABLE	RUNNING VARIABLE:					
	AGE	DEATH AGE				
retD	> 59	ALL	59 - 68	61 - 65	62 – 64	62.5 – 63.5
RD_{ROBUST}: LATE t-value (robust)	**-0.957** (-2.92)***	**-0.932** (-2.77)***	**-0.916** (-2.76)**	**-0.822** (-2.69)**	-0.402 (-0.82)	-0.504 (-0.88)
MSE OPTIMAL BANDWITDH	∓ 1.725	∓ 1.702	∓ 1.678	∓ 0.606	-0.273 0.251	-0.146 0.188
SAMPLE SIZE	58615	6483	2900	1200	656	104
EFFECTIVE SAMPLE SIZE	383, 671	374, 663	371, 657	168, 228	68, 96	51, 51
ORDER OF EST. POLYNOMIAL	3	3	3	1	1	1
RD_{OLS}: LATE t-value (robust) R^2	-	-	-	**-0.395** (-3.15)*** 0.167	**-0.555** (-3.08)*** 0.065	**-0.881** (-3.47)*** 0.035

The **`rdrobust`** method loses its merits when the death age window is set to 62–64 years and 62.5–63.5. This is an outcome of inefficiency of method as it needs large sample to let non-parametric estimation produce reliable results with the efficient number of observations. We appended our RD_{ROBUST} estimations with the following standard linear OLS –estimation of model that is much used in RD analysis

$$retD = \beta_0 + \beta_1(AGE_D - 63) + \beta_2(AGE_D - 63) \times D_{63} + \theta D_{63} + \varepsilon \, .$$

D_{63} is the treatment dummy-variable taking value of 1 after death age of 63 years and value of 0 before it. OLS estimation gives significant estimates at 1% level, but the effect estimates are smaller than the large sample RD_{ROBUST} estimates. Surprisingly, OLS effect with the smallest age window gave estimate (-0.881) close to RD_{ROBUST} estimates. Adding 2nd order polynomial term $(AGE_D - 63)^2$ into the OLS estimation did not make the results different. Thus, although OLS being somewhat biased in RDD's it still can have a role with local small sample sizes. In Table 3., heteroscedasticity robust variance-covariance estimation is conducted with kernel smoothing weights (see Cattaneo et al., 2020a; Catteneo et al., 2020c; Calonico et al., 2017).

4.2. External validity and stability

Above RD estimates on retirement spells are local average treatment effect (*LATE*) estimates, i.e., the treatment effect identified by RD model applies to a small sub-population, persons having death age close around of 63 years. This problem of local can be approached in many ways to increase the external validity of RD estimates. Above we estimated treatment effects for persons retiring after age of 59 years with different death age windows and RD estimation bandwidths. This estimation strategy implies some external validity for RD effect estimates.

Cerulli et al. (2017) propose an interesting stability test (*TED*) for RD estimates that also has external validity implications. The test is based on the idea that we examine the curvature stability properties of the *LATE* RD estimates with different death age values near of 63 years. If stability is not found, we would have serious doubts about the general usefulness and external validity of the RD estimates, since other contexts are likely to differ from the analysed here in even more substantial ways than a marginal change in death age at age 63 years (Cerulli et al. 2017, p. 318).

In technical terms, the sharp RD treatment effect is $\theta(c) = m(c^+) - m(c^-)$, but now we estimate also $\theta'(c) = m'(c^+) - m'(c^-)$, i.e., the derivates of estimated continuous regression functions on both sides of cut-off point. If the derivate values $m'(c^+)$ and $m'(c^-)$ differ much, this means that slopes of treatment levels at $c^- \approx c \approx c^+$ are different, and RD estimate is instable and external validity is questionable. In contrast, having near-zero $\theta'(c) = m'(c^+) - m'(c^-)$ estimates with different bandwidths for continuous functions $m(c^+)$ and $m(c^-)$ provides evidence supporting stability of RD estimates and external validity.

Table 4. gives *TED* estimates with t-values based on OLS-estimation of RD effect observations with different bandwidth values. We don't find any significant *TED* estimates with different bandwidths, i.e., RD effect estimates are stable, and they have some external validity with respect to the cut-off point.

TABLE 4. TED STABILITY TESTS WITH DIFFERENT BANDWITDH (BW) VALUES

OUTCOME VARIABLE: RETIREMENT DURATION	RUNNING VARIABLE: DEATH AGE			
BANDWITDH	63 ∓ 3.00	63 ∓ 2.00	63 ∓ 1.00	63 ∓ 0.50
RD_{OLS}: LATE t-value (robust)	**-0.641** (-2.93)***	**-0.596** (-2.86)***	**-0.824** (-2.84)***	**-0.679** (-2.46)**
TED_{OLS} t-value	0.648 (0.95)	0.555 (1.06)	0.223 (0.15)	-0.586 (-0.64)
SAMPLE SIZE	1823	1200	656	104
ORDER OF EST. POLYNOMIAL	3	2	2	1

4. 3. Covariates

4.3.1. Background

One approach to test the validity of conducted RD analysis is to use the robust RD treatment effect estimation method on potential covariates with the same running variable as in the main RD analysis of interest. If statistically significant effects are found (i.e. discontinuities) in covariates as outcomes, the validity of RD of interest is questioned because covariates may cause the main RD treatment outcome effects. However, if the validity is secured, then the covariates can have a role in canonical RD analysis. The case is however now different, say from standard multivariate OLS regression, and special care is needed here. Cattaneo et al. (2022) note that "When employed correctly, baseline covariates can be useful for the analysis and interpretation of RD designs. First and foremost, canonical RD designs do not necessitate covariate adjustments, and therefore researchers should always report unadjusted RD treatment effect estimates and associated unadjusted robust bias-corrected inference methods in those RD settings. When pre-intervention covariates are available, they can be used for two main purposes without affecting the main RD identification strategy: (i) to improve efficiency and power, and (ii) to define new parameters of interest" (2022, p. 24).

4.3.2. Health, unemployment, and retirement

Terminated retirement spells consist of two components: the age of retirement and the age of death. Both are affected by person's health and the labour market episodes nearing the old age pension age. There exists a vast literature on the relationship between retirement and health with mixed results – typically focusing on the effects of retirement on health (see eg., Pilipiec et al., 2021; Scharn et el., 2018; Swedas et al., 2018). Much less is known in the details how health determines the timing of retirement (Kuhn, 2018; Ilmakunnas and Ilmakunnas, 2018;

Conley and Thompson, 2013). However, we know that poor health has negative effects on person's work and survival prospects.

The case of (long term) unemployment happening before retirement time is even more complex than the above health-retirement nexus. Typically, prolonged unemployment around and after of age 60 years ends with retirement as the probability of re-employment decreases rapidly at the age close to retirement (Marmora and Ritter, 2014; Nichols et al., 2013). However, in countries like Finland where income adjusted unemployment allowances and unemployment social benefits form opportunity costs to pensions, postponing the retirement time can happen. Likewise, the level of allowances for job sickness leave can be higher than the pension level. These social security payments end in most of cases – but not necessarily always – when the person reaches the minimum eligible age of 63 years for old age pension.

On the general level this means that these special labour market episodes (i.e., non-working periods) *before* retirement or death can have discontinuities close to age of 63 years. Now our main outcome variable of interest, the retirement spell length, is expected to be affected by these non-working outcomes. To avoid wrong cause and effect inferences, we next analyse separate RD's for persons who have experienced sickness and unemployment periods before retirement.

4.3.3. RD plots for retirement spells and non-working episodes with death ages

Figure 4. depict RD outcome plots with retirement durations and composite number of non-overlapping days of non-working periods. The non-working periods show a kink in function at death age of 63 years. However, the discontinuity in the smooth function for retirement durations widens when persons with pre-retirement non-working periods are excluded from the sample compared to result with persons having pre-retirement non-working periods.

Table 5. reports the results of RD validation testing with different predetermined and non-predetermined covariates having values before retirement and death (for summary statistics, see Appendix 4). We expect that the random character of our running variable makes

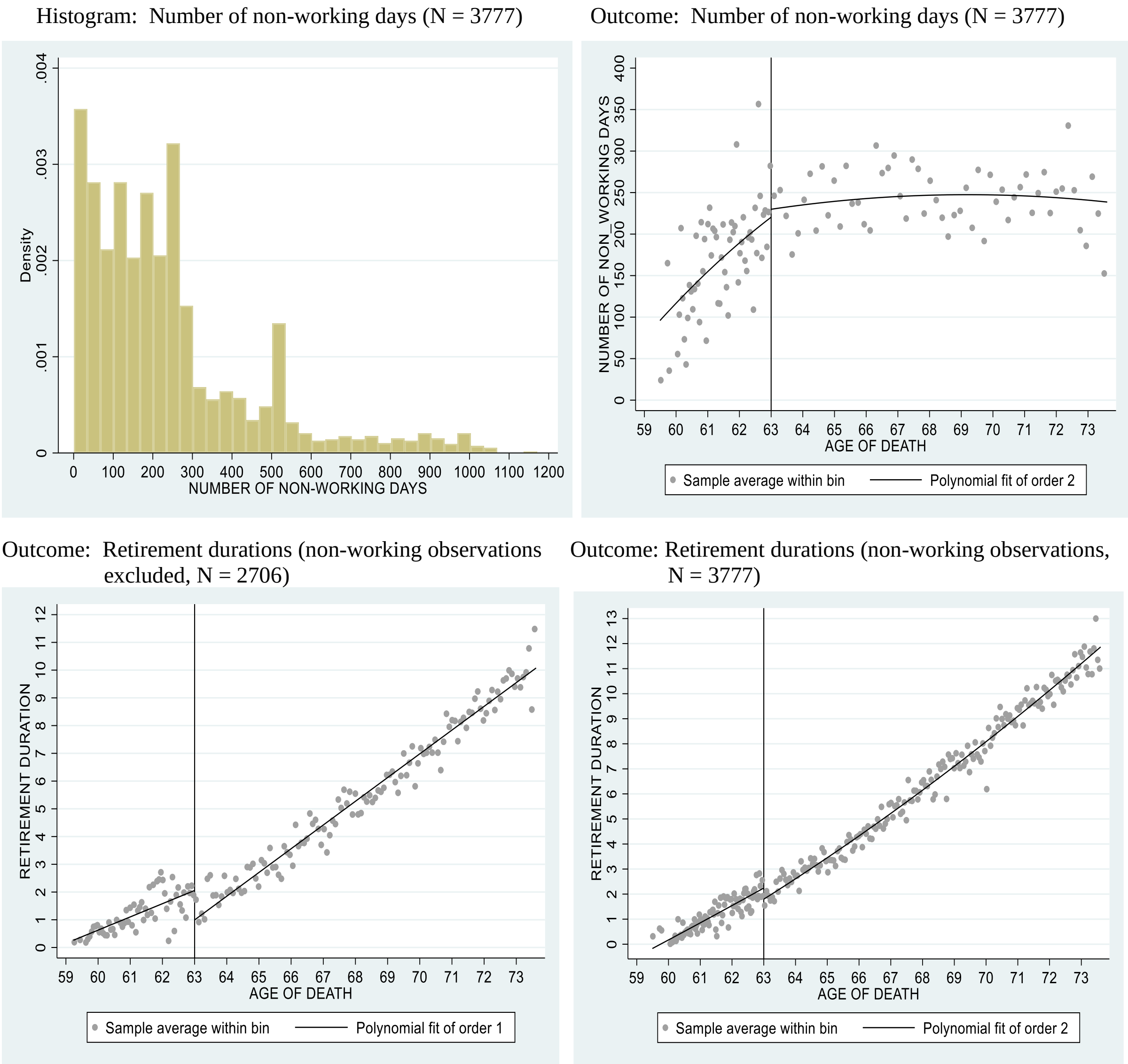

Figure 4. Regression discontinuities in retirement durations and number of non-working days with age of death (59 < AGE_D < 73) as running variable.

discontinuities in covariates not to be present. Note that the sample sizes vary in validation testing because some of covariates were not fully recorded in the data. We used maximum sample sizes for the running variables in the analysis. All considered predetermined covariates pass the validation except the LANGUAGE variable. It is difficult to give interpretation to this result. It has only a minor importance because the share of Swedish speaking persons is only 5 percent in the data.

We mean by non-predetermined or non-fixed variables those that can take different pre-intervention values that conditions the value of outcome variable, i.e., these can affect both the retirement age and age of death. Here our interest is on the mean of yearly incomes before retirement in addition to the number of non-working days analysed above. Note, that pre-retirement incomes are of high importance in life-cycle labour supply models where conditions for the retirement age is derived (see e.g., Bloom et al., 2014; Fields and Mitchell, 1984). We expect that mortality is also sensitive to life cycle incomes as we known that wealth gives more years to live (see e.g., Glei et al., 2022; Benzeval et al., 2014; Smith, 1999). However, both these non-predetermined variables pass the validation test.

TABLE 5. RD_{ROBUST} VALIADATION TESTS FOR COVARIATES

RUNNING VARIABLE	OUTCOME VARIABLE					
DEATH AGE	GENDER	CIVIL STATUS	LANGUAGE	EDUCATION	INCOMES	# NWD[1)]
RD_{ROBUST}: LATE t-value (robust)	-0.162 (-1.59)	-0.045 (-0.31)	**0.163** (2.75)***	-0.137 (-0.69)	1.250 (0.28)	30.452 (0.48)
MSE OPTIMAL BANDWITDH	∓ 1.212	-1.414, 5.159	∓ 0.929	∓ 1.544	∓ 1.516	∓ 1.643
SAMPLE SIZE	6483	6482	6482	6483	4082	3777
EFFECTIVE SAMPLE SIZE	306, 1398	341, 2342	261, 369	353, 597	144, 315	265, 395
ORDER OF EST. POLYNOMIAL	2	2	2	2	2	2

NWD = NUMBER OF NON-WORKING DAYS

When the predetermined covariates are added to retirement duration RD model, the above RD effect results in Table 3. are still valid (see Table 6, RD_1): the treatment effect has value of -0.993 (t-value: -3.08). When the non-predetermined covariates are used the results are somewhat different. When incomes are included in the model (Table 6, RD_2) RD effects estimate is now -1.092 with t-value of -2.89. Using number of non-working days as covariate makes RD effect estimate smaller in absolute value (Table 6, RD_3 and RD_4). The result is expected when the Figure 4. results are considered. Note, that RD estimation for covariates and their augmentation in retirement spell outcome RD estimation can be seen as one form of external validity testing.

TABLE 6. RD_{ROBUST} EFFECT ESTIMATES WITH COVARIATES

	RUNNING VARIABLE: DEATH AGES			
OUTCOME VARIABLE: retD	RD_1	RD_2	RD_3	RD_4
RD_{ROBUST}: LATE t-value (robust)	**-0.933** (-3.08)***	**-1.092** (-2.89)***	**-0.638** (-2.24)**	**-0.555** (-2.13)*
MSE OPTIMAL BANDWITDH	∓ 1.201	∓ 1.862	∓ 1.344	-0.824, 3.071
SAMPLE SIZE	6482	4081	3777	2148
EFFECTIVE SAMPLE SIZE	304, 459	165, 405	243, 331	71, 259
ORDER OF EST. POLYNOMIAL	2	2	2	1

COVARIATES:

RD_1: GENDER, CIVIL STATUS, LANGUAGE, EDUCATION
RD_2: GENDER, CIVIL STATUS, LANGUAGE, EDUCATION, INCOMES
RD_3: NUMBER OF NON-WORKING DAYS
RD_4: NUMBER OF NON-WORKING DAYS, GENDER, CIVIL STATUS, LANGUAGE, EDUCATION, INCOMES

4.3.4. Alternative approaches

Results so far lead to a question "Could we obtain comparable results with some other methods?" Used RD approach shows that retirement durations shorten local close after the death age of 63 years compared to the ages close before of 63 years. Now, if we underline the randomness of death at the age of 63 years, we can calculate means of retirement durations on both sides close to the age of 63 years as estimates for population means. This approach mimics RCT approach and should give corroboration to RD results if the results are not conflicting with RD estimates. Alternative we can stress the fact that our outcome variable, the terminated retirement spell, contains also other component, i.e., retirement age, that is affected by personal characteristics and labour supply factors. This means that we should control for these before we can analyse the age of death mean effects on retirement spells.

Method of regression adjustment (*RA*) is suitable approach to make control and treatment groups comparable (e.g., see Imbens and Wooldridge 2009, Section 5.3). RA is based on a two-step approach to estimating treatment effects. First, we fit separate regression models of the outcome on a set of covariates before and after death age of 63 years (i.e. control and treatment groups). Second, we compute the averages of the predicted outcomes for *each subject* in both groups. The contrasts of these averages provide estimates of the average treatment effect (*ATE*). RA estimators are consistent if the treatment is independent of the potential outcomes after conditioning on the covariates. It is important to report summary statistics of the covariates by treatment status to secure that distributions of covariates are in balance on both sides of the treatment. Table 7. reports RA results along with sample differences in means with t-values in small death age bandwidths close to the death age of 63 years. Estimates in Table 7. are not conflicting the earlier RD estimates. The effect estimates are smaller in absolute values compared to RD estimates, but they tend to increase when the age window gets smaller.

TABLE 7. RA TREATMENT AND SAMPLE MEAN DIFFERENCE ESTIMATES WITH DIFFERENT DEATH AGE WINDOWS

OUTCOME VARIABLE: retD	$62 < AGE_D < 64$	$62.5 < AGE_D < 63.5$	$62.75 < AGE_D < 63.25$
RA_{ATE} 1)	**-0.509** (-2.60)***	-**0.612** (-2.23)**	-**0.895** (-2.98)***
SAMPLE SIZE	85	47	32
$MEAN_{>63} – MEAN_{<63}$	-0.128 (-0.73)	**-0.597** (-2.08)*	**-0.843** (-2.38)**
SAMPLE SIZE	204	74 2)	46

1) Covariates: GENDER, CIVIL STATUS, LANGUAGE, EDUCATION, INCOMES

2) $62.6 < AGE_D < 63.4$

Appendix 5. gives some covariate balance statistics. They show that large non-balances are not present. Note, that number of non-working days is not included as a covariate in RA modelling because when added to analysis the sample sizes are too small for efficient estimation.

4.3.5. Who are the persons having short retirement durations around the death age of 63 years?

Above we showed that persons who die close *before* the eligible minimum old age pension age will experienced longer retirement spells in average than those who die close *after* this age albeit they have also retired in average before age of 63 years. We argued above in Section 2.2. that persons can avoid lowest eligible old-pension age with other forms of pension arrangements before age of 63 years, and then move later-on to the old-age pension system. We also showed with our RD validity and covariance balance testing that persons had at the cut-off point of age of 63 years equal personal and economic characteristics. This leads to the conclusions implied by our RD analysis that (death) age of 63 years treats persons in inequal way with respect to terminated retirement durations.

With reference to the pension types at the cut-off age we observe (see Appendix 6, Tables 6A-6B) that 87 percent of those *retired after* age of 63 years had old-age pension as their *last* form of pension, and 49 per cent of those who *retired before* age of 63 years had some other form of pension as their *first* pension type. The related pension type frequencies among those who *not-survived* and *survived* beyond the age of 63 are 92.1 and 95.6 per cent (Tables 6C-6D). These findings along with Table 2. and RD model results imply that persons having short terminated retirement durations close to death ages after age of 63 years are old age pension takers but those with somewhat longer durations but dying before age of 63 years have some other form of pensions as their first pensions. These are in most of cases persons that are allowed for (work) disability, part-time, and unemployment pensions. This leads to argument that the Finnish pension system produces with the statutory age limits undesirable outcomes for some retirees that must conflict their retirement intentions. In other words, some old age pension takers deceasing close after age of 63 years have experienced shorter retirement spells compared to persons that have allowed for other forms of pensions with earlier retirement ages.

5. Conclusions

RDD analysis with retirement duration as outcome variable and retirement death age as a running variable among Finnish retirees was conducted. Analysed data consisted of person data with year 1947 birth cohort during the follow-up period of 1.1.2007 – 31.12.2019. For the year

1947 cohort the eligible old-age pension age window is between ages of 63 and 68 years. However quite many persons retire before the minimum age of 63 years for different reasons. The age of 63 years as a limit is a natural cut-off age in this context, and we proposed a research question "Has the death happening around the retirement age of 63 years an effect on the length of retirement duration?" A positive – but surprising – answer was obtained to the question with conducted RD analysis across the different sub-samples with respect to retirement spells, retirement ages, and death ages.

On the general level the results show that retirees who survive close to *above* the age of 63 years have shorter retirement spells than those who die close to *below* age of 63 years. This non-intuitive result depends on the retirement age behaviour difference between the groups: survivors close past the age of 63 years retire later than ones close before age of 63 years. Detailed analysis showed that other forms of retirement (e.g., disability and unemployment pensions) sustain the observed longer retirement durations compared to retirees having old-age pension starting at age of 63 years as their only pension arrangement. Our main result implies that the minimum age of eligible retirement age of 63 years has acted as an unfavourable limit in terms of retirement spells for some retirees among the Finnish year 1947 birth cohort. We can't argue that this outcome corresponds to their retirement intentions and plans.

The point estimates for robust RD effects were in the range from –1.09 to –0.56 of year in duration loss depending on the used sub-samples and RD regression estimation method. In addition, regression adjustment (RA) methods and raw differences in means testing provided supporting evidence for RD model estimates. Finally, some external validity test values and RD model alternatives with covariates indicated that results are robust and have external validity.

Our RD model can be compared to local RCT's as our running variable, the age of death, is a random variable. This does not put so big stress on RD estimates as local effects as the identification can be based also on randomness around the cut-off age, not as a limit result of potential outcomes. Note that, the randomization-based RD approach (see Catteneo et al. 2022d), not necessarily the continuity-based RD framework, is considered almost as credible as random experiments. However, Sehkon and Titunik (2016, 2017) show that it is hard to defend (local) RD estimates – either based on randomization or continuity – as genuine randomized treatment effects.

Appendix 1. Data sources and variable summary statistics

Person level register follow-up data. Starting 1.1.2007, ending 31.12.2019.
Statistics of Finland: birthday in year 1947, date of death, gender, civil status, language, education
ETK (Finnish Centre for Pensions): date of retirement, pensions, incomes
KELA (The Social Insurance Institution of Finland): number of days of unemployment, number of days of sickness leave
Main variables of interest: AGE_D = *age of death*,
retT = retirement age of 1st pension type ($\geq$ *59 years*)
retD = composite retirement duration of allowed pensions

The number of births in year 1947 was 108.168. At the starting day of sample (1st of January 2007) 80.003 persons were still alive and had a Finnish citizenship. 19.867 of these had retired before the 1st of January 2007. These survivors were *not* included in the study because the dates of deaths are observed only after 1st of January 2007. This means that including observations with retirement ages before of age of 59 years would give biased measures of terminated retirement durations. In addition, 1521 person had obscure retirement status after age of 59 years. These cases were also dropped from the analysis. The analysed sample consist of 58.615 persons. As our focus is on retirement behaviour around the age of 63 years, we use cases that are exposed to death risk close to age of 63 years.

Table 1A. Number of death retirees

	Freq.	Percent	Cum.
DEATH	6,483	11.06	11.06
ALIVE	52,132	88.94	100.00
Total	58,615	100.00	

Table 1B. First pension type

1st PENSION	Freq.	Percent	Cum.
OLD-AGE	35,879	61.21	61.21
OTHER	22,736	38.79	100.00
Total	58,615	100.00	

Table 1C. Last pension type

LAST PENSION	Freq.	Percent	Cum.
OLD-AGE	56,236	95.94	95.94
OTHER	2,379	4.06	100.00
Total	58,615	100.00	

Table 1D. Summary statistics of main variables with last pension

	Obs	Mean	Std. Dev.	Min	Max
OLD-AGE PENSION					
AGE_D	56,236	68.75	2.92	59.72	73.62
retT	56,236	62.55	2.06	59.00	72.38
retD	56,236	10.27	2.56	0.08	14.68

OTHER PENSION					
AGE_D	2,379	63.06	3.08	59.06	73.39
retT	2,379	61.58	1.03	59.00	64.68
retD	2,379	8.58	4.28	0.00	14.52

Appendix 2. RD manipulation test with different sub-samples

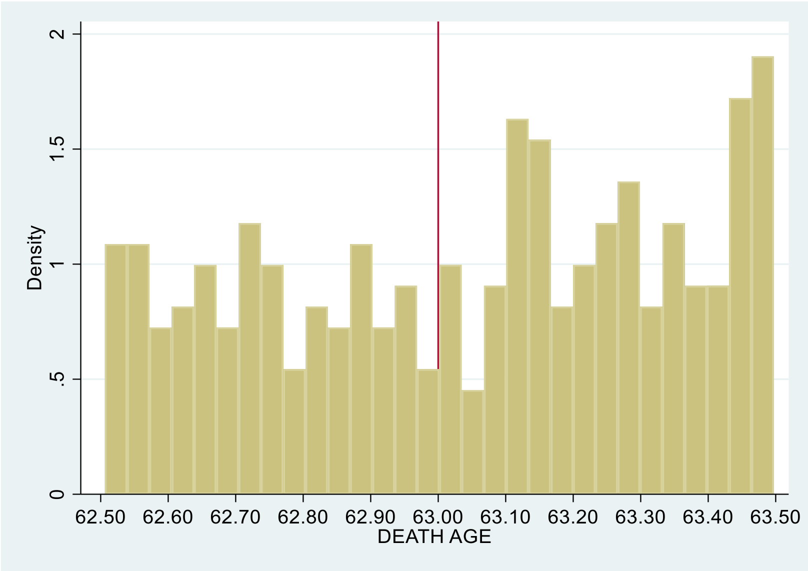

Figure A2-1. HISTOGRAM OF DEATH AGES (62.5 < AGE < 63.5, N = 334)

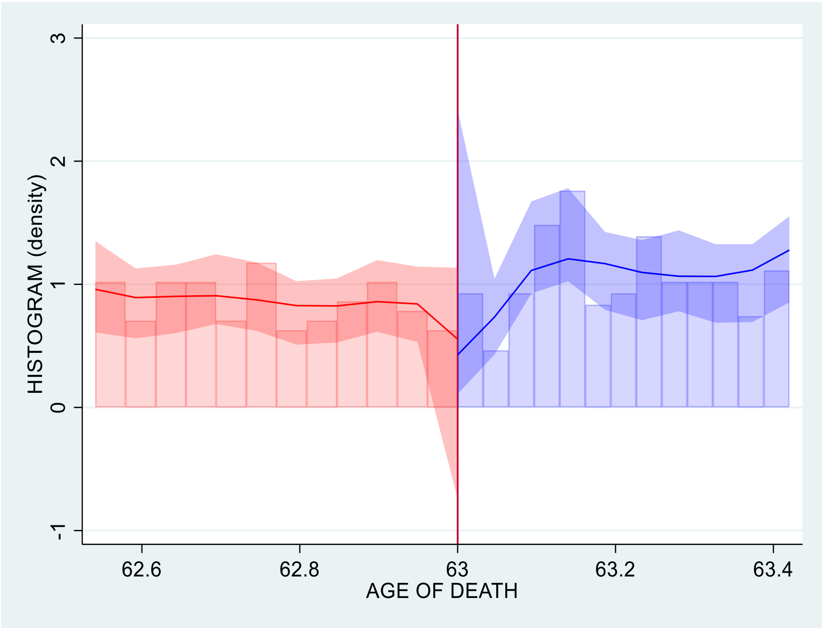

Figure A2-2. MANIPULATION TEST PLOT (62.5 < AGE < 63.5, N = 334)

TABLE A2. RD MANIPULATION TEST USING POLYNOMIAL DENSITY ESTIMATION
(kernel = triangular, VCE method = jackknife)

	AGE_D = 63 with retT > 59, N = 58615 (Left of cut-off: 569, Right of cut-off: 58046) Order of polynomial = 2	
	BW_{OPT}= -1.78, 1.33	BW = ∓ 2.00
N_{EFF}	(395, 511)	(422, 778)
TEST $VALUE_{ROBUST}$	0.557	1.445
P-VALUE	0.571	0.148
	AGE_D = 63 with retT > 59, AGE_D < 72, N = 5537 (Left of cut-off: 569, Right of cut-off: 4968) Order of polynomial = 2	
	BW_{OPT}= -1.66, 1.41	BW = ∓ 0.50
N_{EFF}	(388, 647)	(143, 191)
TEST $VALUE_{ROBUST}$	1.069	0.238
P-VALUE	0.285	0.773
	AGE_D = 63 with retT > 59, AGE_D < 68, N = 2900 (Left of cut-off: 569, Right of cut-off: 2331) Order of polynomial = 2	
	BW_{OPT}= -1.37, 1.33	BW = ∓ 0.25
N_{EFF}	(326, 525)	(66, 89)
TEST $VALUE_{ROBUST}$	0.524	-1.099
P-VALUE	0.600	0.272

N_{EFF} = effective (binned) sample sizes on the left and right side of the cut-off point
BW = bandwidths of estimation around the cut-off point with binned data

Appendix 3. Number retirees and deaths in different age groups

AGE	RETIREES	DEATHS	RETIREES/DEATHS
61.00	167	31	5.38
61.25	176	35	5.02
61.50	145	36	4.02
61.75	114	32	3.56
62.00	300	49	6.12
62.25	373	70	5.32
62.50	117	57	2.05
62.75	103	77	1.33
63.00	**613**	**66**	**9.28**
63.25	**787**	**89**	**8.84**
63.50	151	102	1.48
63.75	156	99	1.57
64.00	113	96	1.17
64.25	102	87	1.17
64.50	69	98	0.70
64.75	67	112	0.59
65.00	139	95	1.46

Appendix 4. Pre-determined covariates (death retirees)

GENDER

	Freq.	Percent	Cum.
MALE	4,192	64.66	64.66
FEMALE	2,291	35.34	100.00
Total	6,483	100.00	

CIVIL STATUS

	Freq.	Percent	Cum.
UNMARRIED	1,005	15.50	15.50
MARRIED etc.	3,185	49.14	64.64
DIVORCED	1,659	25.59	90.23
WIDOW	633	9.77	100.00
Total	6,482	100.00	

LANGUAGE

	Freq.	Percent	Cum.
FINNISH	6,157	94.97	94.97
SWEDISH	326	5.03	100.00
Total	6,483	100.00	

EDUCATION

LEVEL OF EDUCATION	Freq.	Percent	Cum.
BASIC	2,817	43.45	43.45
SECONDARY	2,205	34.01	77.46
TERTIARY	762	11.75	89.22
LOWER ACADEMIC	368	5.68	94.89
HIGHER ACADEMIC	331	5.11	100.00
Total	6,483	100.00	

Non pre-determined covariates (death retirees)

MEAN YEARLY INCOMES BEFORE RETIMENT (1000 Euros)

Variable	Obs	Mean	Std. dev.	Min	Max
INCOMES	4,082	18.37	16.92	0	430.59

NUMBER OF DAYS OF NON-WORKING DAYS (NWD)BEFORE RETIREMENT

Variable	Obs	Mean	Std. dev.	Min	Max
NWD	3,777	237.11	211.56	1	1170

Appendix 5. Covariate balance testing (Austin, 2009)

62 < DEATH AGE < 64 (N = 104)

Variable	Mean Treated	Mean Control	%bias	t-test t	t-test p>|t|	VAR(Treated)/ VAR(Control)
GENDER	1.2519	1.2754	-5.3	-0.36	0.719	0.94
CIVIL STATUS	2.1926	2.058	16.0	1.07	0.284	1.10
LANGUAGE	1.0667	1.1014	-12.5	-0.87	0.384	0.68*
EDUCATION	2.1333	2.2029	-6.2	-0.42	0.672	0.88
INCOMES	18.669	16.659	14.1	0.65	0.518	1.14

* if variance ratio outside [0.71, 1.41]

62.5 < DEATH AGE < 63.5 (N = 47)

Variable	Mean Treated	Mean Control	%bias	t-test t	t-test p>|t|	VAR(Treated)/ VAR(Control)
GENDER	1.1897	1.3043	-26.6	-1.36	0.177	0.72
CIVIL STATUS	2.1897	2.1304	7.0	0.35	0.726	1.21
LANGUAGE	1.0517	1.087	-13.8	-0.71	0.481	0.61
EDUCATION	2.1552	2.087	6.3	0.32	0.752	1.22
INCOMES	21.082	17.995	20.2	0.67	0.506	1.10

* if variance ratio outside [0.59, 1.69]

62.75 < DEATH AGE < 63.75 (N = 32)

Variable	Mean Treated	Mean Control	%bias	t-test t	t-test p>|t|	VAR(Treated)/ VAR(Control)
GENDER	1.2143	1.2778	-14.4	-0.48	0.631	0.82
CIVIL STATUS	2.2143	2.0556	18.4	0.60	0.551	1.31
LANGUAGE	1.0714	1.0556	6.4	0.21	0.836	1.24
EDUCATION	2.0012	1.7778	24.2	0.78	0.439	1.59
INCOMES	19.105	16.691	21.2	0.42	0.677	2.69*

* if variance ratio outside [0.46, 2.16]

Appendix 6. Pension type summary statistics (death retirees)

Table 6A. First pension type at retirement age of 63 years (N = 6483)

BEFORE AGE OF 63 YEARS

1st PENSION TYPE	Freq.	Percent	Cum.
OLD-AGE	3,165	48.82	48.82
OTHER	3,318	51.18	100.00
Total	6,483	100.00	

Table 6B. Last pension type at retirement age of 63 years (N = 6483)

AFTER AGE OF 63 YEARS

LAST PENSION TYPE	Freq.	Percent	Cum.
OLD-AGE	5,703	87.97	87.97
OTHER	780	12.03	100.00
Total	6,483	100.00	

Table 6C. First pension type at death age of 63 years (N = 6483)

BEFORE AGE OF 63 YEARS

1st PENSION TYPE	Freq.	Percent	Cum.
OLD-AGE	45	7.91	7.91
OTHER	524	92.09	100.00
Total	569	100.00	

Table 6D. Last pension type at death age of 63 years (N = 6483)

AFTER AGE OF 63 YEARS

LAST PENSION TYPE	Freq.	Percent	Cum.
OLD-AGE	5,657	95.65	95.65
OTHER	257	4.35	100.00
Total	5,914	100.00	

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