Lifetime Income Inequality: quantile treatment effect of retirement on the distribution of lifetime income.

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May 15, 2017

Abstract

Recent reforms in pension systems, enacted in most European countries, aim to extend working lives, shortening years spent in retirement, consequently reducing the period of withdrawing retirement benefits. As can be motivated from both theoretical and empirical standpoint, these changes are by far going to reshape individual income profiles, and consequently affect inequality in lifetime income. This study attempts to estimate the causal effect of staying longer in the labor force on the distribution of lifetime income and to assess its consequences for overall inequality in lifetime income. Results for cross-national setting are estimated through Local Quantile Treatment Effect estimator by Abadie, Angrist and Imbens (2002), and are confronted with the Instrumental Variables Quantile Regression by Chernozukov and Hansen (2005). Relevant country specific estimates rely on Frandsen, Frölich and Melly (2012) approach. While the results of cross-national setting clearly suggest heterogenous effect across the distribution, negative at the bottom tail, increasing in magnitude across the quantiles, the results of country specific estimates are less readable.

Key words: Income inequality; Lifetime income; Social Security Systems; Aging; SHARE; Quantile Treatment Effects ;

JEL codes: D31, I32

*Corresponding address: Malgorzata.Karolina.Kozlowska@gmail.com. I would like to thank to Franco Peracchi, Alberto Abadie, Francesco Andreoli, Josh Angrist, David Drukker and Philippe van Kerm for valuable comments and insightful discussions. This paper uses data from SHARELIFE release 1, as of November 24, 2010, and from SHARE release 2.5.0, as of May 24, 2011. The SHARE data collection has been primarily funded by the European Commission through the 5th, 6th and 7th Framework Programmes. Additional funding also came from the U.S. National Institute on Aging as well as from various national sources.

1 Introduction

One of the implications of the Permanent Income Hypothesis (PIH) is that reducing the share of income that is transferred through Social Security Systems increases life cycle inequality. As explained by Deaton et al. (2002) the mechanism of redistribution in income caused by changes in social security settings relies on the fact that any entitlement program acts as an insurance instrument which pools the earnings risk, limiting evolution of economic inequality over life cycle and consequently reducing inequality in lifetime resources. Public pension systems are typical examples of social insurance arrangements which provide substantial risk sharing over life cycle. Any changes in pension schemes affecting shares of annuities in total income are supposed to affect individual lifetime resources, altering redistribution and inequality.

Recent reforms in pension systems, enacted in most European countries, aim to extend working lives, shortening years spent in retirement, consequently reducing the period of withdrawing retirement benefits. As can be motivated from both theoretical and empirical standpoint, these changes are by far going to reshape individual income profiles, and consequently affect inequality in lifetime income.

As implied by Human Capital Earnings Function (HCEF), which evidences fanning out of earnings profiles across education groups as the cohort ages, extending working lives is supposed to impact differently individual earnings paths at different income levels. While highly educated well-offs are likely to benefit from extending their careers, continuing drawing their educational wage premia, for the unskilled poor, whose pensions are expected to replace relatively high share of their earnings, the perspective of working longer may seem less attractive. Deaton and Paxon (1994) states explicitly that within the PIH framework "disparities in earnings between groups with different schooling levels grow in retirement age". Extending working lives for additional years is thus likely to further deepen the divide between the well-qualified and those less educated.

The redistributive effect across income groups entails further consequences for the overall inequality in lifetime resources. Economic theory motivated by human capital models, PIH, as well as more general models of intertemporal choice indicates that the within-cohort inequality evolves over the life-cycle, reaching the highest levels at the older age. Extending working lives for additional years is thus likely to exacerbate further this pattern, spreading out the inequality in lifetime resources. Such result would be also consistent with the implications of Deaton's idea that inequality is the consequence of individual risk in income. Decreasing the role of pensions in total lifetime resources lowers the degree of risk sharing provided by social security, and should be associated with increased redistribution.

Reconsidering the effect of the reforms in the context of Social Welfare Theory reinforces the view that postponing retirement enhances disproportions between different socio-economic groups. Public pensions are the most evenly distributed social security benefits. In lifetime perspective they tend to be progressive, with higher ratios of lifetime benefits to lifetime contributions for low earners, compared to high earners. By Pigou-Dalton Principal of Transfers any (mean-preserving) progressive transfer, ensuring redistribution of resources from higher to lower income groups, should decrease inequality and improve social welfare. Scaling down progressivity of pension systems through decreasing shares of retirement benefits in total lifetime income is thus supposed to entrench inequality in lifetime resources.

However, departing from the infinite horizon assumption, invoked by most theoretical models, from the perspective of the true reform design, the effect may seem less clearly meaningful, given that postponing retirement for two years, as envisaged by most policy reforms, prolongs working careers by small percentage only. Notwithstanding, the redistributive consequences of recently enacted changes in retirement polices may be considerable for several reasons. First of all, for individuals with high growth rate of wages, most income is reaped in the end of the life cycle, and pre-retirement earnings are around the highest in the working carees. Thus for them deferring exit from work for each year should be rewarded with a notable proportionate increment in lifetime earnings. As for low wage earners an option of working one more year may be less favourable, the income gap is supposed to increase, elevating noticeably disparities within the most unequal cohort. Second, the effect of progressivity of transfer program on decrease in income inequality depends both on the degree of progressivity and size of the program (Coronado at all. 2000). Even modest reduction of progressivity of pension schemes, associated with seemingly minor trimming of pensions-earnings ratio in lifetime dimension, is supposed to entail considerable consequences for the overall inequality in lifetime resources due to large size of retirement programs.

Overall the non negligible effect of postponing retirement on lifetime resources, heterogenous across different parts of the distribution of lifetime income should seem unambiguous. It would thus be highly relevant to understand the pattern of changes induced by the reforms.

This study attempts to estimate the distributional causal effect of staying longer in the labor force on lifetime income and assess its consequences for overall inequality in lifetime resources. It focuses on 11 European countries facing the problem of population ageing, struggling to conform swelling ranks of retirees with sustainability of social security systems. Specifically, it attempts to address the following research questions: What is the redistributive effect of staying longer in the workforce on lifetime income? What is the effect of delaying retirement on inequality in lifetime resources ? How are the reforms going to affect social welfare? The topic of this study is exceedingly relevant in terms of its utility for policy making, taking up enduring questions revolving around recently enacted reforms in pension systems. The results of the analysis provide important insights into understanding unanticipated consequences of the reforms, which except for entailing (disproportionate) impact on economic well-being of elderly, may raise the level of relative deprivation associated with lowering social welfare. The work sheds also some light on the mechanisms underlying increasing inequality, linking changes in social security and lifecycle dynamics to growing disproportions between the social groups.

Despite the policy relevance of the topic, the empirical evidence on the consequences of changes in social security setting for income inequality is scarce. Recent developments in the related literature focus on studying various aspects of overall increase in the dispersion of earnings observed in industrial countries, devoting relatively little attention to the role of non-wage components.

In principle there are two major difficulties associated with measuring precisely the effect of changes in statutory retirement age on the distribution of lifetime income and inequality. The first lies in the methodological aspect. As the association between the retirement age and lifetime income is clearly endogenous, simple quantile or distributional regressions are likely to be biased and uninformative. In order to identify the causal effect of interest there are needed instrumental variable techniques adjusted to distributional framework, which until recently were unavailable. Another challenge concerns scarcity of datasets suited for studying lifecycle phenomena, especially those involving measure of financial resources. Deriving a comprehensive measure of lifetime income requires rarely available londituginal data on individual earnings spanning entire working lives. Reliance on cross-sectional data is unsatisfactory, mostly due to the fact that point-in-time measures of earnings do not reflect dynamic nature of wages, and are unlikely to approximate lifetime income profiles.

This study proposes to estimate the causal effect of retirement age on the distribution of lifetime income, addressing the issue of endogenity through recently developed quantile instrumental variables techniques that exploit variation in institutional background of retirement polices (differenced with the actual age of respondents in the year of the interview) as instruments. It employs data from the Survey of Health, Ageing and Retirement in Europe (SHARE), a unique dataset that contains retrospective information on individual employment histories and provides self reported values of earnings in crucial moments in the careers, setting the ground for deriving individual lifetime income trajectories and calculating a reliable measure of lifetime income.

This work improves over the existing literature in several more respects. It seems to introduce a novel approach in linking changes in social security programs and inequality through causal effects, employing recent advances in quantile regression techniques. It also adds to the lifecourse literature by providing evidence on the heterogenous effect of retirement on lifetime resources in a multi-country setting.

It builds upon three strands of the literature. The first is the classical Human Capital Literature. Seminal studies by Becker (1964,1967), Ben-Porath (1967), Mincer (1978) set the link between education, labor market experience, and wages. Numerous later studies enhance understanding of this relationship, emphasizing its consequences for the overall inequality.

The second concerns works investigating linkages between social security and inequality, as well as evolution of inequality over life-cycle. Kotlikoff (1990), Panis and Lillard (1996), Coronado at all., Deaton at all. (2000) emphasize explicitly the redistributive impact of social security on income. In the growing literature on the dynamic nature of inequality over the life-cycle, works by Deaton and Paxon (1994) and Blundell (2014) contribute importantly to understanding its consequences for the old age resources.

Finally, the third is the econometric literature setting background for estimating redistributive effects of the programs. Whereas seminal studies by Abadie (2000), Abadie, Angrist and Imbens (2001), Chernozukov and Hansen (2005), Frandsen (2008), Frandsen, Frölich and Melly (2012), introduce the proper econometric framework within which to analyze redistributive causal effects, Abadie (2003) and Chernozukov and Hansen (2004) (2013) exemplify application of the recent advances in quantile regression techniques to estimate the effects of participation in social security programs on the distribution of wealth.

The remainder of this paper is organized as follows. Section 2 reviews econometric framework proposed to address research question of this study. Section 3 describes the dataset used, discusses problems associated with the survey and briefly summarizes the procedure of deriving the variable of main interest, a measure of lifetime income. It also presents basic descriptive statistics. Section 4 introduces identification strategy adopted. Section 5 provides the results obtained through different estimation techniques. Section 6 verifies sensitivity of the results to alternative specifications of the model. Section 7 concludes.

2 Estimation framework

This section reviews recent developments in quantile treatment effect estimation techniques, methods employed to address the empirical questions of this study. It briefly describes the estimation procedure and reviews underlying assumptions and interpretation of three estimators most likely to accommodate the research questions.

Estimation and identification of quantile treatment effects under endogenity builds upon two main streams of the literature. The first one, Abadie, Angrist and Imbens (2002) allows estimating local quantile treatment effect of a binary variable, using binary instrument. The second, Chernozukov and Hansen (2005) estimate population quantile treatment allowing for non-binary treatment and instrument. Building upon these two approaches there have been developed quantile instrumental variable techniques settling quantile treatment effect in a regression discontinuity design. Frandsen, Frölich and Melly (2012) introduce an estimator for local quantile treatment in a regression discontinuity design, while Guiteras (2008) develops a quantile treatment effect estimation in regression discontinuity framework based on Chernozukov and Hansen.

2.1 Quantile Treatment Effect

Considering estimation of the causal effect of a binary treatment D on the distribution of outcome Y, the starting point is the conditional quantile function :

$$Q_p(Y_D|X) = \alpha_p D + X'\beta_p \tag{1}$$

where: Y_D is a potential outcome , α_p is the effect of the treatment (a coefficient of interest), and X is a vector of additional regressors. Exploiting properties of invers transformation method it can be represented as:

$$Y_D = \alpha(U_D)D + X'\beta(U_D), \quad U_D|X \sim \mathcal{U}(0,1) \tag{2}$$

In the absence of sufficient argumentation ruling out endogenity of D, estimating (2) through conditional quantile regression of Koenker and Bassett (1978) leads to inconsistent estimates, confounding causal interpretation of the estimated effect of the treatment on an outcome variable.

Specifying quantile function of latent outcome variable Y_D as in (2) we obtain Structural Responce Function of the form:

$$S_Y(p, D, X) = Q_p(Y_D|X) = \alpha(p)D + X'\beta(p), \qquad D \in \{0, 1\} \tag{3}$$

Using Instrumental Variable approach, under different set of assumptions, the two most appealing approaches to estimate the causal effect of the treatment $\alpha(p)$ as the difference in the p-th quantile of the marginal distribution of potential outcomes:

$$Q_p(Y_1|X) - Q_p(Y_0|X) = 1^*\alpha(p) + X'\beta(p) - 0^*\alpha(p) - X'\beta(p) = \alpha(p) \tag{4}$$

2.2 Abadie, Angrist and Imbens (2002)

Abadie, Angrist and Imbens (2002) introduce an approach to estimate a causal effect of a binary variable on the distribution of an outcome using a binary instrument.

Identification of the causal effect is achieved for the population of compliers, these individuals whose treatment status can be manipulated by the instrument, and relies on a set of assumptions, essentially similar to those underlying identification of Local Average Treatment effect. The principal assumption, Independence (Y_1, Y_0, D_1, D_0 is jointly independent of $Z|X$), requires that the instrument is as good as randomly assigned, and that potential outcomes are not directly affected by the instrument. It implies that in the population of compliers comparison by D|X define the causal effect of D on Y. The second assumption, Nontrivial assignment ($P(Z = 1|X) \in (0, 1)$) states that each individual has some chance to be assigned to treatment group and some chance to be assigned to control group. The First Stage condition ($E[D_1|X] \neq E[D_0|X]$), likewise in LATE, requires non zero average causal effect of Z on D. Finally, the Monotonicity condition ($P(D_1 \geq D_0|X) = 1$), although that untestable, desires that individuals who are affected by the instrument, are affected in a monotone way.

Under the above assumptions, in the population of compliers the conditional quantile function equals the quantile causal responce function:

$$S_{Y|D_1>D_0}(p, D, X) = Q_p(Y|D, X, D_1 > D_0) = \alpha(p)D + \beta X'\beta(p) \tag{5}$$

The QTE for compliers is than given by:

$$QTE(p) = Q_p(Y_1|X, D_1 > D_0) - Q_p(Y_0|X, D_1 > D_0) = \alpha(p) \tag{6}$$

In the context of the empirical questions of this study, applying Abadie, Angrist and Imbens' approach is associated with a few inconveniences. First, unlike 2SLS, local Quantile Treatment Effect framework does not allow for continuous treatment, Even if the primary focus of this work is on comparing two groups, and research questions can be perfectly answered by a model with binary specification of the variable of interest, possibility of estimating directly the effect of retirement age or years spent in workforce on lifetime income would allow extending the scope of the study, and could serve as a robustness check of the results from the basic specification. Another disadvantage concerns the fact that this framework estimates the quantile specific effect for the subpopulation of compliers and not for the population as a whole, as desired. Also, estimated treatment effects cannot be interpreted as individual effects. Unless a strong assumption of rank invariance is plausible, the estimates allow drawing conclusions about changes in the distribution but not distribution of changes.

In turn, assumptions underlying identification should be successfully fulfilled. The independence assumption is successfully fullfilled if the instrument employed is 'as good as randomly assigned'. As variation in institutional background satisfies this condition, using as instruments changes in early and normal statutory retirement ages ensures that potential outcome and potential treatment assignment are indpendent of the instrument. Differencing the retirement eligibility age with actual age as of the year of the interview is supposed to comply to the assumption, as long as actual age is not the predictor of the outcome per se, and is not likely to be correlated with other determinants. Nontrivial assignment assumption is realized as long as there are country dummies included, and year of birth does not fully determine treatment assignment status. The evidence for the first-stage validity will be presented later in the paper. Finally, monotonicity condition, is expected to hold, as changes in retirement ages induce individuals in the same way.

2.3 Chernozukov and Hansen (2005)

Chernozukov and Hansen (2005) present a Quantile Instrumental Variable estimator for a population as a whole. They propose a solution to estimate Quantile Treatment Effect as a quantile causal response function through a population moment condition. The five underlying assumptions identify the causal effect of the treatment.

The Potential Outcomes condition assumes that Y_d can be related to its quantile function $q(d, x, \tau)$ as $Y_d = q(d, x, \tau)$ with $U_d \sim \mathcal{U}(0, 1)$ with an imposition of strict monotonicity in τ and U_d. The second condition, Independence, requires that potential outcomes are independent of $Z|X$. The third assumption concerns treatment selection mechanism. It defines D as an unknown function of X and Z, and an unobserved random vector V which determines treatment status across individuals with identical observable characteristics. The strongest condition of Rank Invariance, possibly reduced to rank similarity, requires that ranks U_D do remain unchanged across the potential treatment status, implying that the unobserved component U determines the individuals' ranking across the treatment states. The more general version of the assumption , rank similarity, relaxes strict rank invariance by allowing unsystematic variations of U_d conditional on X, Z and V. Both rank invariance and rank similarity in many empirical applications may be implausible. The last condition simply states that the observed variables consist of $Y = q(D, X, U_D)$, $D = \delta(Z, X, V)$, X and Z.

Embedding empirical question of this study in QIV framework by Hansen and Chernozukov is associated with a couple of advantages. First of all the estimator is suited for discrete and continuous treatments and instruments, which allows specifying endogenous variable in a convenient way. Other benefits associated with estimating QTE within this framework are that obtained estimates are representative for the population as a whole, and that under rank invariance condition they may be interpreted as individual effects.

However, analyzing the assumptions underlying estimation and identification of the model in the context of the research question renders application of the model troublesome.

While independence assumption can be successfully fullfilled if the instrument adopted relies on institutional changes in retirement regulations (or its adequate modifications), rank invariance or rank similarity condition are less likely to be plausible. One of the reasons for which the distribution of U_D is likely to differ across the treatment status may be that typically pension-earnings replacement rate is less than one, effecting in higher overall income from lifetime perspective of individuals who work longer. Also actuarially adjusted systems tend to penalize premature withdrawal from the labor force.

Keeping in mind the limitations of the assumptions imposed by Hansen and Chernozukov approach, a model settled in this framework will be estimated in order to verify its assumptions and confront its results with the results obtained using the alternative technique by AAI. Though the model allows continuous treatments , to keep common framework there will be applied the same model specification with binary endogenous variable.

2.4 Frandsen, Frölich and Melly (2012)

Frandsen, Frölich and Melly (2012) adapt Abadie, Angrist and Imbens (2002) approach to obtain consistent estimate of local quantile treatment effect settled in a regression discontinuity framework. The motivation for the new QTE estimator suited for RD design is the fact that in finite samples a naive application of LQTE by Abadie et al. in a RD framework may suffer from substantial bias.

The bottom line of the RD framework is introduction of a running variable R determining treatment status in a discontinuous way when it falls above or below a pre-defined cut-off value r_0. Thus the indicator for the eligibility for treatment is defined as $Z_i = 1(R_i >= r_0)$, and treatment status is denoted $D_i = D_i(R_i)$. Applying naively Abadie, Angrist and Imbens (2002) would imply exploiting $Z_i = 1(R_i >= r_0)$ as the instrument for treatment D. However, in sharp RD design, in finite samples such instrument conditional on running variable R is deterministically "0" or "1", which would violate "Non trivial assignment" condition of LQTE. On the other hand, as argued by Frandsen et al., not conditioning on R leads to a kind of omitted variable bias. Also as another sort of bias there was pointed out boundary bias coming from implicitly estimating quantile functions at a boundary.

Frandsen et al. propose to estimate the local quantile treatment effect in RD approach as the horizontal difference between the marginal distributions of the potential outcomes for compliers at a particular quantile at the cutoff of the running variable.

$$\alpha(p) = Q_{Y^1|C,R=r_0}(p) - Q_{Y^0|C,R=r_0}(p) \tag{7}$$

Identification of the treatment effect relies on four assumptions. The principal assumption establishing regression discontinuity design is that the probability of receiving treatment changes discontinuously at the cut-off value of the running variable. ($\lim_{r \to r_0^+} Pr(D = 1|R = r) > \lim_{r \to r_0^-} Pr(D = 1|R = r)$) The second, smoothness condition consolidates two assumptions of the local average treatment effect in RD design. First, it requires that all factors determining the outcome variable (other than R), are continuous with respect to r (at r_0) ensuring that outcome of individuals just below the cut-off value can be considered counterfactual for individuals just above the cut-off. Second requirement captured by the smoothness condition is that no manipulation over treatment assignment takes place, which ensures that the treatment is as good as randomly assigned around the cut-off. The next assumption, monotonicity, likewise in Abadie at al. (2002), requires that the response to treatment assignment among affected individuals is monotone. Eventually, the final condition requires that observations close to the cut-off r_0 exist. Based on the above assumptions the discontinuity gap at the cut-off identifies the treatment effect of interest.

The major advantage of settling the research question of this study in the RD framework is that it allows examining distributional effect of staying longer at the labor force on lifetime income at a country level, which may be of principal interest of policy makers. Nevertheless such specification is also a subject to a number of constraints.

First of all it requires confining attention to only those countries which experienced a notable change in retirement policy, as for the other countries the RD defining assumption of discontinuity in the probability of receiving treatment is violated. Further it is associated with a few similar concerns as the estimator by Abadie at all (2002). The country level estimates, although that consistent, are only local estimates in the population of compliers, and unless a rank invariance assumption is reasonable they cannot be interpreted as individual effects. Further, given that in the studied case the treatment is a subject to a birthday cutoff eligibility rule, and that running variable is the date of birth, this case stands slightly apart from the classical RD framework. The difference between the standard RD design and a design with time as running variable lies in the validity of tests examining identification assumptions. The standard verification tests, such as test of smoothness in baseline covariates, may be not interpretative. Individual characteristics defined prior to the assignment threshold, will be by assumption the same just below and above the cutoff, and hence lack of discontinuity in these variables at the threshold is uninformative.

Analyzing the rest of assumptions underlying identification of the model does not bring any further distress about applicability of the estimator. The Regression Discontinuity assumption intuitively should be successfully fulfilled as the major reforms in pension systems are aimed at changing retirement behaviour of elderly, consequently affecting probabilities of retirement at relevant age thresholds. The assumption will be elaborated in more details in the following chapter. A part of the smoothness condition concerning perfect control over the assignment variable is satisfied by construction, as there is no possibility of manipulation of assignment variable such as year of birth. Monotonicity condition, as discussed before is untestable but intuitively plausible.

All in all the country level estimates based on Frandsen at all. (2012) framework will be estimated for countries which experienced a change in statutory retirement ages in order to validate results obtained hitherto.

3 Data

This section describes the data used, starting with the micro level database SHARE, followed by the description of the source of information about instruments used. Finally it drafts the procedure of constructing the outcome variable, a measure of lifetime income.

3.1 SHARE database

The micro data come from the Survey of Health, Ageing and Retirement in Europe (SHARE), a random longitudinal sample focused on the European population aged 50 and over. At the moment of this study the survey consists of three regular panel waves and the life history questionnaire SHARELIFE, collected accordingly in 2004-2005, 2006-2007, 2010 and 2008-2009. The longitudinal dimension of the survey spans 13 countries from all regions of Europe: North (Sweden and Denmark), Central West (Austria, Belgium, France, Germany, The Netherlands, Sweden, Switzerland), South (Spain, Italy and Greece) and East (Czech Republic and Poland). Moreover the survey is harmonized with the English Longitudinal Study of Ageing (ELSA) and the U.S. Health and Retirement Study (HRS), which allows extending the range of the research based on common framework to two more countries.

Primarily used sample in this study is the second wave and SHARELIFE, in some cases completed with information drawn from the other two waves. While the second wave provides the data on personal characteristics and some of current income statements, SHARELIFE provides detailed information on entire employment history of respondents including amounts of earnings and social benefits received in decisive moments in life, making ground for recovering individual lifetime income trajectories.

The main advantages of using SHARE data in this study are its crossnational and multidisciplinary dimension allowing for comparison of lifecourse inequality phenomenon across many countries characterized by different economic structures and labor markets with diverse social security settings. Richness of information about individuals' lifetime employment history and labor force transitions providing statements about compensation and social benefits at certain points in the past makes it a unique dataset for studying labor economics phenomena relying on lifetime resources. However lack of continuity of earnings history of respondents implies the need to predict lifetime income, which is the major challenge associated with using SHARE. A brief description of prediction of lifecourse income is provided in the next subsection.

3.2 Instruments

Although that variation in institutional background of retirement rules is commonly employed as instruments in the literature, a comprehensive summary of changes in statutory retirement ages which took place in Europe in recent years is not easily available. While normal retirement ages for males, which experienced relatively few changes over time, are well documented, the evidence on early retirement ages is not systematic. The detailed information on changes in normal and early retirement ages is collected through surveying various sources. The main reference for description of retirement regulations in cross- country setting are series of NBER publications "Social Security Programs and retirement around the world" (1999), (2004), (2010), web publications by U.S. Social Security Administration "Social Security Programs Throughout the world", and works by Duval(1998) and Blondall, Scarpetta(1999). However a complete picture of changes especially in early pension eligibility requires referring to country specific publications. Tabulation of early and normal retirement ages, and a brief description of the major reforms affecting pension eligibility ages dating back to 1967 can be found in Appendix A.

3.3 Lifetime income

The measure of lifetime income adopted in this study includes lifetime earnings from work and work-related retirement pensions from the public pension systems. Due to the purpose of this study it focuses on these two work-related income components only, not reflecting other potentially important elements of lifetime income such as social pensions, disability benefits, transfers, profit earned through income generating assets. Since private pensions may be considered as long-term savings are neither considered in income measure, confining the definition of pensions to state provided retirement benefits.

This version of the study only considers individuals who at the time of the interview are retired, so both their retirement age and first pension benefit received is known. Restricting the sample in this way allows avoiding bias coming from predicting retirement age and replacement rate. Consequently, the measure of lifetime income exploited in this study is represented by the following formula:

$$Y_i = \sum_{t=1}^{R_i} s_{t+1}\omega_t W_{it} + \sum_{R_i+1}^{110} s_{t+1}\omega_t P_{it}$$

where Y_i is total lifetime income, W_{it} is lifetime earnings from work at age t, P_{it} is lifetime retirement pension at age t, R_i is retirement age, s_{t+1} is probability of surviving to age t+1 and ω_t - discount/capitalization rate.

Particular components of the formula are derived in the following way. Modeling of the data is preceded with extensive data cleaning process aiming at eliminating unfeasible values reported in the survey, given that quality of the raw data is of crucial importance for accuracy of further estimates. The cleaning procedure reveals two systematic patterns associated with misreporting income values. Data for countries which experienced currency exchange, as well as statements referring to earlier work spells tend to be of notably lower accuracy. Rigorous assessment of quality of raw data, based on both economic and statistical criteria (comparison against minimum wage and assessment of interrelation of statements based on factor analysis),ensures reliability of the income amounts used in predicting final measures of lifetime income. All these amounts are converted to common currency referring to one point in time through applying relevant exchange rates, CPI and PPP indexes. The measure of lifetime earnings is derived following the Human Capital literature, based on an extension of the standard Mincer equation. There is estimated a median regression model of logarithm of reported earnings, linear in schooling and quartic in experience. The quality of predictions is evaluated based on cross-validation and bootstrap estimate of prediction error. Individual earnings paths, are derived according to commonly used HCEF prediction model. Taking advantage of the monotone equivariance property of quantile regression predictions of earnings in logarithms are retransformed back to predictions in levels.

Lifetime pensions are derived based on the assumption of constant real pension benefits, which appears to be appropriate for most countries considerd. Both future earnings and future pensions are weighted by survival probabilities. Survival Probabilities are predicted following the methodology proposed by Peracchi and Perotti (2010), which relies on Lee-Carter model (1992) introducing life expectancy forecasting algorithm based on SVD decomposition.

Earnings and pensions are discounted to age 50 at a conventional rate 2%. The choice of the age to which the earnings are discounted changes the value of lifetime income, however it does not influence the ranking of individuals in the lifetime income distribution, an aspect of principal importance for this study.

3.4 Sample selection and descriptive statistics

The analytical sample of this study focuses exclusively on male individuals, employed in the non farming sector, who at the moment of the interview were retired. Its size is determined by availability of information necessary to construct individual income trajectories. Under such selection criteria the sample consists of 2438 observations. Table 1 lays out the size of the total sample and of country specific subsamples with breakdown by retirement age, a variable of interest for the sake of this analysis. It shows that there is a high number of individuals who withdrew from the labor market prematurely, and a small, but notable group of individuals working much longer than envisaged by standard retirement age. As income trajectories of these individuals may be influenced by their unusual retirement behaviour, those who retired before age 55 or after 70 are excluded from the sample. After this additional criterion the number of available observations is reduced to ca. 2250, which is relatively small for accurate assessment of distributional effects. In an ideal setting, resembling the design of the reforms enacted recently in European countries, the sample shall be constrained only to the individuals retired exactly at age 63 and 65. Such a setting would simulate introduction of a policy forcing everyone to retire two years later, as planned in most countries. However, the relatively small size of the overall sample encumbers evaluating the effect of retirement age of two cohorts splitted up by the difference of exactly two years in retirement age. Thus, the analysis will focus on comparison between the two groups of 'early' and 'late' retirees, defined by the cutoff age 62. In the baseline setting the group of 'early' retirees pools individuals who retired between 55 and 62 years of age, while the group of 'late' retirees comprises individuals retired between 63 and 70 years of age.

While Figure 1 gives a general overview on the distribution of lifetime income in the total sample and each of the countries considered, Figure 2 depicts the densities of lifetime income for the two retirement age groups of early and late retirees. The densities are estimated through kernel method using a Gaussian kernel function and a bandwidth optimal for Gaussian kernel and Gaussian data. On each of the curves there are marked out values corresponding to the bottom and the top fifth percentile of the distribution.

The comparison of the two groups of early and late retirees reveals several interesting features. It clearly shows that the distribution for late retirees tends to be more spread out than for early retirees. Typically, the values corresponding to the top 5th quantiles of the distribution for late retirees lie above the corresponding value for the group of early retirees, while the bottom 5th quantiles for the late retirees lie systematically below the corresponding values for the early retirees. Consequently, the distance between the upper and the bottom 5th quantiles is higher for the group of individuals working longer, suggesting that there is more inequality among individuals staying longer in the workforce rather than for those withdrawing earlier. Table 2 provides the exact values corresponding to the relevant quantiles of the two distributions, reporting also 95/5 quantile ratios, which can be interpreted as simple measures of dispersion. The measure for the group of retired later is remarkably higher than for the group of retired earlier. Such a picture provides the support for the conjecture that extending working lives is associated with higher inequality. Moreover, it can be concluded that the increase in the inequality, can be attributed to both rising the upper part of the distribution, and decreasing the bottom. However, as the presented descriptive statistics do not account for selection effects, likely to be the case, they should be interpreted with caution.

4 Model specification and identification

This section describes strategy adopted to identify the causal effect of postponing retirement to later ages in two approaches: cross-national, settled in QIV framework, and country specific, settled in QRD design. It presents specification of the two models considered, gives an account of the major identification issues underlying estimation of the causal effect of interest, and elaborates on the strategies adopted to remedy the principal identification problem, endogenity, in the context of the research questions and the dataset employed.

4.1 Cross-national Setting

4.1.1 Model Specification

As discussed before, all models considered attempt to estimate the effect of staying longer in the workforce on the distribution of lifetime income. An ideal specification addressing the research problem at hand would involve as treatment a binary indicator, comprising exclusively individuals retired at age 65 as the 'treatment' group, and those retired at 63 as the 'control group'. However limitation of the sample size enforces generalizing the treatment to a dummy variable indicating more broadly retiring 'later' or 'earlier'. Consequently, the core variable of interest is constructed as an indicator of retiring before or after the predefined threshold age. As the cut-off age there is selected age 62, given that it splits the total sample as well as country sub-samples in relatively comparable proportions. Although the framework by QIV-ChH is suited for categorical and also continuous treatments, for comparability reasons for both models the same specification is considered. Namely:

$$Y_i = \alpha_0 + \alpha_1 R_i + \beta^\top X + \varepsilon_i \tag{8}$$

where Y_i is personal lifetime income, R_i is a binary variable taking value 1 if an individual retired exactly at age 63 or later, and 0 if an individual retired by age 62, and X contains set of country dummies.

4.1.2 Endogenity issues

A fundamental problem in estimating the effect of retirement age on the distribution of lifetime income casting doubt on causal interpretation of ordinary quantile regression is endogenity. There are at least three nonnegligible reasons motivating concerns of endogenity. The first is selection bias. Namely, individuals who decide to stay longer in the labor force, to begin with may differ in terms of personal characteristics from those who withdraw from the market prematurely. A more general problem of omitted variable bias resulting in heterogenity in labor-leisure preference at the moment of retirement is also nonnegligible. Yet another reason posing a serious risk of engodenity is reverse causality. It can be simply motivated by the fact that retirement decisions are usually the outcome of utility maximization problem, resolved by evaluation of option value of continuing to work and retiring, which depends on the proportion of earnings and pensions.

4.1.3 Identification

Identification strategy adopted relies on instrumental variables techniques, exploiting as instruments cohort specific legislated early and normal retirement ages differenced with the actual age of respondents in the year of the interview. Specifically, the instrument is defined as a binary variable taking value 1 if the distance between the earliest legal retirement age and actual age is equal to or strictly greater than 3, and 0 if the distance is less than 3. Formally,

$$\begin{cases} \text{Z=1}, & \text{if } \mathrm{A}_i - leg_{ER} \geq 3 \\ \text{Z=0}, & \text{if } \mathrm{A}_i - leg_{ER} < 3, \end{cases}$$

where A_i is the actual age as of the year of the interview, and leg_{ER} is the earliest legal retirement age in force in the year of retirement. The tabulation of legal retirement ages used for the construction of the instrument can be found in the appendix A.

The instrument adopted is supposed to be a good instrument, successfully satisfying exclusion restriction and first-stage condition. Even if exogenity assumption is essentially untestable, conceivably the instrument chosen is likely to fulfil it, as the only channel through which the distance between age and pension eligibility age may affect lifetime income is its impact on retirement decisions and factual retirement age, rendering exclusion of the instrument from the main equation valid.

Moreover, both of components used in construction of the instrument considered separately (A_i and leg_{ER}) are arguably exogenous and correlated to the treatment variable. Shifts of statutory retirement ages (leg_{ER}) are driving retirement behaviour of elderly and are naturally correlated to actual retirement age. They are also clearly independent of potential outcomes and are not supposed to affect lifetime income through any other channel than retirement age. Actual age of respondent in the year of the interview (A_i) is also supposed to be as good as randomly assigned. It is not expected to be correlated with any of the determinants of lifetime income, either observed or unobserved, other than retirement age.

Overall, it can be fairly concluded that the instrument adopted is supposed to identify the effect of staying longer in the labor force, implying causal interpretation of estimated quantile treatment effects.

4.2 Country specific setting

In the light of recently implemented and adopted by many countries policies postponing early and normal retirement ages, the principal interest of most policy makers is assessment of its consequences at a country level. Proper evaluation of the causal effect of changes in statutory retirement ages on economic outcomes, i.e. inequality, in a country specific framework is of crucial importance due to the fact that retirement policies, although that tend to be standardized across Europe, are regulated by countries' governance authorities at a country level.

4.2.1 Regression Discontinuity Design

Redistributive effect of retirement on income in a country specific setting is embedded in a RD framework. The motivation for such framework is that in the absence of experimental design at a country level the causal effect of retirement may be identified exploiting changes in statutory retirement ages which took place in recent decades in European countries. Variation in retirement eligibility rules induces discontinuous changes in the probability of retirement at the threshold ages, which constitutes an ideal background for quasi experimental design. The evidence will be provided for these countries which are supposed to satisfy the defining condition of RD, namely presence of discontinuous change in the probability of treatment at the threshold value of the running variable. Treatment D_i in this setting will be defined as an indicator for remaining in the workforce beyond a given age, a discontinuity defining threshold age determined by policy changes. Running variable B_i, influencing the probability of treatment will be the date of birth. $Z_i = 1(B_i >= b_0)$ will be a dummy variable indicating meeting eligibility age for a given retirement scheme.

4.2.2 Changes in statutory retirememt ages

Six out of ten countries considered in the cross-country analysis experienced major changes in early or normal retirement ages. Except for Denmark, which in 2004 experienced a change of normal retirement age lowering it from 67 to 65, and Italy, which shifted gradually normal retirement age from 61 to 65 over 90-ies, in the other five countries there occurred major changes only in early retirement ages. Austria increased the ER age from 60 to 62, implementing the change gradually throughout the years 2002 - 2006. As the cutoff threshold defining discontinuity there is adopted age 61, which came in force in the first phase of the reform, in 2003. In Sweden and in Spain the early retirement ages were raised from 60 to 61, with changes coming into force in 1998 and 2002 accordingly. In Switzerland, a major change decreasing ER age from 65 to 63 was phased in over years 1997 - 2001. The cut-off threshold defining discontinuity is set to 63, which is a legal early retirement age from 2001. In case of Denmark, although that there was a change in the normal retirement age, as the discontinuity defining change in pension eligibility rules there will be exploited the change in early retirement age rising it from 50 to 60 years old, implemented in 1996. In case of Italy, there will be exploited one of the reforms in normal retirement age, and the cut-off value considered age 65, which commenced its legal force in 2000.

Regardless to whether the change inducing discontinuity in probability of retirement is a change in normal or early retirement age, both lead to a fuzzy regression discontinuity design, given that the treatment status is not deterministically related to the threshold crossing rule.

4.2.3 Model Specification

General specification of the model considered is roughly the same as in the cross-country setting, just the specification of variables is suited to the examined approach. The following model is estimated separately for each country considered:

$$Y_i = \alpha_0 + \alpha_1 D_i + \beta^\top X + \varepsilon_i \tag{9}$$

where Y_i is personal lifetime income, D_i is a binary variable taking value 1 if an individual retired at or beyond the relevant cut-off threshold , and 0 if an individual retired before, and X contains set of cohort dummies.

5 Empirical results

This section presents the results obtained by a set of models introduced above, first laying out conclusions drawn from the cross-national setting, followed by conclusions from the country specific framework. The starting point of the discussion is ordinary least squares (OLS) followed by conventional instrumental variables model (2SLS). As the benchmark model for further consideration there is estimated ordinary quantile regression model (QR). Then there are presented results of principal interest, estimates obtained through two quantile instrumental variable techniques. First there is presented the evidence from local quantile treatment effect by Abadie, Angrist and Imbens (QTE-AAI), compared with the results obtained through quantile instrumental variables following Chernozukov and Hansen approach (QIV-ChH). Finally, for countries which experienced changes in statutory retirement ages in recent years there is provided evidence based on quantile treatment effect in regression discontinuity design by Frandsen, Frölich and Melly (RDDQTE), confronted with results obtained by applying QTE-AAI in a regression discontinuity design.

5.1 OLS, 2SLS and Median regression

Table 4 presents the results of the baseline OLS and 2SLS models confronted with ordinary QR estimates. Coefficient of interest from OLS suggests positive association between staying longer in the workforce and lifetime income. The conjecture of the positive relationship is supported by roughly five times stronger average effect estimated through 2SLS, which is presumed to identify the causal link, accounting for endogenity of retirement decisions. However, median regression with its slightly negative coefficient contradicts such picture, suggesting an adverse relationship between the two variables at the center of the distribution. Nevertheless, none of the estimates is statistically significant.

With regards to control variables, estimates for country dummies from all three models (OLS, 2SLS and QR(.50)) are consistent, revealing a systematic pattern in effects across the countries.

5.2 Quantile regression

The first column of table 5 and figure 3 illustrate in details the decomposition of the average effect across specific quantiles of lifetime income. The figure shows that the average effect obtained from OLS overestimates the median effect, keeping up with QR estimates somewhere around the 55th percentile of the outcome distribution. Looking at the estimates across the quantiles of the distribution there is clearly visible location-scale association between staying longer in the workforce and lifetime income, implying that there exist important differences in its effects throughout the distribution. A slightly negative estimate at the median implies a small downward shift in location. The negative estimate at the lower tail, becoming positive around the 50th percentile, and rising further up the distribution result in an upward sloping curve, indicating positive scale effect. Shifting down the bottom quantile of the distribution while raising the top suggests that postponing retirement to higher age exaccerbate the overall lifetime income inequality. However, as quantile regression estimates not necessarily have causal interpretation, the evidence based on the techniques combining quantile regression with causal inference will be examined.

5.3 Quantile causal effect

Estimating causal effect of staying longer in the workforce on the distribution of lifetime income through LQTE in the population of compliers gives quite similar results to those from QR, though with larger standard errors, rendering estimates insignificant throughout the major part of the distribution. Upon reestimation of the model with bootstrapped standard errors with 50 replications estimates at 5th, 15th, and 20th percentile turn into significant. Given that increasing number of replications (to 100 and 200) does not enhance significance of the parameters unambiguously, the estimates with 50 replications bootstrap remain as optimal. The results are reported in the second column of table 5 and are depicted by figure 4. Likewise the previously reported QR estimates, LQTE coefficient are negative at the lower tail, increasing throughout the distribution, revealing clearly upward trend. Unlike QR, which surpasses the zero line just right upper the median, LQTE remains negative up to around 70th percentile, although that the shape of the two curves is remarkably similar, with the LQTE coefficients consequently lagging behind QR throughout of the whole distribution. The upward sloping curve implies a conclusion that, in the population of compliers, staying longer in the workforce has redistributive effect on lifetime income, which in turn suggests increase in the overall inequality of lifetime income. Despite bootstrapping, standard errors remain pretty large, rendering estimates significant only at a few quantiles, and making confidence intervals fan out at the upper part of the distribution.

The last two columns of table 5 and figure 5 confront estimates from QIV-ChH with LQTE. The results show that while the general pattern suggesting upward trend of the effect throughout the distribution resembles the effect from LQTE, there is a notable difference in the magnitude of the effects. Whereas QIV-ChH underestimates LQTE markedly up to around the median, between the 50th and 70th quantile the pattern of both estimators is remarkably similar, in the upper part of the distribution coefficients of the estimator for the whole population tend to be higher than of the LQTE. Interestingly, coefficients from both of the estimators become positive around the same 70th quantile. Moreover, the estimated by QIV-ChH are more precise. Whereas they are statistically significant throughout the lower part of the distribution, and at a few quantiles in the upper part, LQTE are insignificant over the whole distribution, except for a few bottom quantiles. All in all, QIV-ChH estimates lead to essentially the same conclusion as ordinary QR and LQTE about redistributive effect of staying longer at workforce on lifetime income, deepening the divide between the richest and the poorest, consequently increasing inequality in lifetime resources.

Moreover, following Chernozukov and Hansen (2004), similarity of results of LQTE and QIV-ChH suggest two important implications. First it may be concluded that assumptions underlying both models are plausible, including rank similarity or rank invariance. Second it advocates that subpopulation of compliers is a fair representation of the overall population.

Estimates of controls for countries, reported at the median only (at the bottom of table 5) are quite consistent across the ordinary quantile regression and the two quantile treatment effect models. Setting Germany as the reference, the estimates for Denmark, France, Sweden and Switzerland are significant and positive for all three models, while for Austria, Italy, Spain, the Netherlands and Belgium they are negative, with large standard errors for the two last countries. However, as estimates for controls cannot be interpreted as causal, they leave room for estimation of the country specific effects of retirement age on the distribution of lifetime income settled in a regression discontinuity design.

5.4 Regression discontinuity design

Regression discontinuity estimates from a country specific setting give two important insights into the effects of retirement age on the distribution of lifetime income. First, at the country level there is clearly visible redistributive effect of staying longer in the workforce, heterogenous across the quantiles of the outcome distribution. Second, notable heterogenity of the effects across the countries characterized by different pension systems suggest a major role of retirement eligibility rules in shaping patterns of inequality. Tables 6 and 7, and figure 6 depict in details the quantile treatment effects from the RD design disaggregated at a country level. Figure 7 plots the estimates together with confidence intervals. While for Austria, Sweden, Italy and Spain RD design suggest a damping effect of continuing working longer, in Denmark and Switzerland the effect is reversed. The estimates for Denmark remain close to zero in the middle, and become positive at the top of the distribution. Switzerland reveals a clearly redistributive effect of staying longer in the workforce, exaccerbating overall inequality, with strongly negative effect at the bottom tail, increasing across the quantiles, turning into positive at the top. Unlike for the other countries, results for Switzerland are statistically significant.

Confronting the RD-QTE results with the results of AAI-QTE approach applied to a RD design it appears that while at the bottom quantiles, typically the estimates are similar, at the top quantiles they tend to diverge. Switzerland remains an exception, where the pattern of the two estimators is reversed throughout the distribution.

The RD design results are quite consistent with the country dummies estimates from the cross-country setting.

6 Robustness checks

The results provided thus far seem to be plausible and consistent with economic theory. However in order to ensure structural validity of the model the estimates should be tested in terms of their sensitivity to various assumptions underlying estimation strategy. This section presents a set of checks implemented to verify robustness of core regression coefficients to modifying different aspects of adopted estimation strategy.

First there is tested stability of the results to changes in estimation framework, switching from the novel quantile instrumental variables techniques, to a simpler, more commonly applied approach relying on average effects estimated separately for subsamples defined by equal-sized intervals of the outcome distribution. Table 8 lays out the results of estimation of average effects of retirement age on lifetime resources separately for quintiles of lifetime income. OLS, 2SLS and Median regression results yield support for previous finding about redistributive effect of retirement age on lifetime resources. Average effects increasing in magnitude across quintiles resemble the upward sloping trend of the coefficients from quantile regression techniques. Consistency in sign and magnitudes between estimated average effects and corresponding quantile effects strongly supports the conclusion about reliability of results obtained from the model embedded in the quantile causal effect framework.

Next there is verified binary specification of the dependent variable and instrument adopted in the study. Encouraged by the conclusions driven in the previous section about plausibility of assumptions underlying QIV-ChH, I estimate the model taking directly retirement age as the dependent variable and instrumenting it with a continuous indicator, a distance from the earliest retirement eligibility age $DistE_i = max\{Age_i - E_i\} + 1$. The results of estimation of the model under such specification, presented in the table 9, reinforces the view that staying longer in the workforce has heterogenous redistributive effect on the distribution of lifetime income. Similarly to the results from section 5, the coefficients for the bottom quantiles are negative, increasing throughout the distribution, becoming positive in the upper tiles. The difference in the magnitude of coefficients, much reduced with respect to the estimates from the baseline models, can be attributed to difference in interpretation of the coefficients.

Another concern, that potentially could cast doubt on the interpretation of the results of the model settled in a multi-country framework is heterogenity of the effects by country, associated with significant differences in the design of retirement policies among European countries. As confirmed by results from RDD framework, country heterogenity seems to be an important issue. In order to control for influence that single countries exert on the overall results, and ensure that the multi-country result is not driven by one country I estimate a set of models excluding single countries from the overall sample. Special focus is put on countries characterized by significantly different retirement policies or retirement behaviour than the majority, such as: France (normal retirement age 60), Sweden (regressive system) , Austria (very high prevalence of early retirement). In most cases the results do not diverge much from the baseline multi country setting.

Finally, the reliability of the inference strongly relies on accuracy of the measure of lifetime income adopted in this study. The measure is a predicted variable per se, and it only approximates the true value of lifetime income. Such measure is imperfect by nature, and some of the assumptions underlying the procedure of deriving the individual income trajectories may influence the overall result. However, the sample used in this study is confined to individuals who reported sufficient information about their careers so as to avoid imposing too strong and not well justified assumptions concerning for instance retirement age, or replacement rate. Minor changes to the procedure of deriving the income profiles, such as changed age to which income is discounted as well as increasing discount rate from 2% to 3 %, resigning from using (SHARE provided) PPP indices does not influence significantly the results of estimation of the relationship between retirement age and lifetime resources. Extensive and precise data cleaning process seems to have played an important role in preserving robustness of results to minor changes in the data. Notwithstanding, changes in major assumptions underlying estimation of lifetime income, such as resigning from Mincer specification in favour of numerical interpolation, or imputing income for individuals who did not report any valid amount, might affect the results.

Overall, it can be concluded that the estimated regression coefficients from the models presented in Section 5 can be reliably interpreted, assuming sufficient certainty about the measure of lifetime income used in this study.

7 Conclusions

This paper examines the effect of staying longer in the labor force on the distribution of lifetime income, accounting for possible endogenity issues. The resulting estimates obtained through two recently developed quantile instrumental variable techniques suggest clearly heterogenous, redistributive effect of postponing retirement to later ages across the quantiles of lifetime income in the overall sample. Surprisingly, similarity of results by the two estimators, QTE-AAI and QIV-ChH suggest that assumptions underlying both estimators are plausible, and that subpopulation of compliers is a fair representation of the overall population. While country specific estimates give less clearly readable results, in the overall sample there is evident indication that postponing retirement to later ages exaccerbates inequality in the lifetime income.

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Table 1: Retirement age by country

	54-	*55*	*56*	*57*	*58*	*59*	*60*	*61*	*62*	*63*	*64*	*65*	*66*	*67*	*68*	*69*	*70*	*71+*	*Total*
Austria	23	7	8	9	15	10	23	15	9	3	4	6	1	1	0	1	1	0	136
Germany (BRD)	19	6	8	9	16	14	57	17	28	43	14	36	3	2	3	1	1	1	278
Sweden	7	10	2	3	7	12	23	13	21	28	18	77	9	3	0	5	4	5	247
Netherlands	4	6	8	15	15	18	45	33	28	11	6	43	2	1	0	0	1	1	237
Spain	17	6	7	8	6	6	26	9	15	4	14	52	3	3	0	1	0	0	177
Italy	101	26	35	32	26	25	40	15	10	11	4	27	6	3	3	1	2	1	368
France	22	25	19	15	17	16	103	24	9	7	5	8	0	1	1	0	0	1	273
Denmark	22	0	5	3	3	8	60	22	33	24	11	18	8	6	1	0	2	3	229
Switzerland	2	2	4	3	8	3	19	7	18	15	11	57	3	4	1	1	6	2	166
Belgium	29	17	27	24	33	18	69	19	15	5	7	54	5	2	1	0	0	2	327
Total	246	105	123	121	146	130	465	174	186	151	94	378	40	26	10	10	17	16	2438

Table 2: Descriptive statistics

	Ret age 60-62				Ret age 63-65			
Country	*q(05)*	*q(50)*	*q(95)*	*q(95)/q(05)*	*q(05)*	*q(50)*	*q(95)*	*q(95)/q(05)*
Austria	4.91	5.63	6.51	1.33	5.27	5.83	7.07	1.34
Germany (BRD)	5.07	5.72	6.34	1.25	4.87	5.82	6.60	1.36
Sweden	5.28	5.98	6.82	1.29	4.81	5.90	7.09	1.48
Netherlands	5.06	5.80	6.43	1.27	4.53	5.66	6.14	1.36
Spain	4.23	5.17	6.10	1.44	4.16	5.16	5.79	1.39
Italy	4.65	5.38	6.25	1.34	4.25	5.24	6.43	1.51
France	4.85	5.82	6.91	1.42	5.15	5.93	6.88	1.34
Denmark	5.14	6.04	6.85	1.33	4.89	6.04	6.87	1.41
Switzerland	5.90	6.61	7.22	1.22	5.91	6.46	7.00	1.18
Belgium	5.10	5.76	6.48	1.27	4.85	5.66	6.56	1.35
Total	4.82	5.73	6.66	1.38	4.57	5.79	6.83	1.38

Table 3: First Stage Regression Diagnostic.

First-stage regression summary statistics				
R-sq.	*Adjusted R-sq.*	*Partial R-sq.*	*F(1,2430)*	*Prob > F*
0.2187	0.2145	0.0242	60.1804	0.0000

Min eigenvalue statistic
60.1804

2SLS Size of nominal 5% Wald test				
	10%	15%	20%	25 %
	16.38	8.96	6.66	5.53

Table 4: OLS, 2SLS and Quantile Regression estimates.

Independent variable:			Quantile regression		
Lifetime Income	OLS	2SLS	.10	.50	.90
Treatment	10.8	53.0	-22.3***	-2.1	54.8*
	(11.3)	(50.9)	(7.3)	(9.5)	(33.0)
Austria	-28.8	-16.9	-37.9***	-51.4***	43.8
	(26.1)	(29.7)	(14.2)	(15.4)	(74.8)
Belgium	9.8	18.1	-3.0	-5.7	33.0
	(20.3)	(22.6)	(11.7)	(12.2)	(42.3)
Denmark	141.6***	142.1***	20.9	121.6***	286.1***
	(22.1)	(22.1)	(29.4)	(15.5)	(65.0)
France	116.8***	131.9***	-6.3	47.2***	297.3***
	(21.5)	(27.9)	(14.2)	(16.8)	(76.5)
Italy	-85.2***	-72.9***	-69.7***	-87.9***	-83.1**
	(20.0)	(24.6)	(10.9)	(14.3)	(36.1)
The Netherlands	-8.7	-5.2	-8.7	9.1	-28.3
	(21.9)	(22.3)	(13.1)	(12.9)	(43.3)
Spain	-161.6***	-163.5***	-118.8***	-155.8***	-202.1***
	(23.8)	(24.0)	(11.2)	(14.6)	(37.2)
Sweden	168.1***	159.1***	16.4	77.2***	351.8***
	(21.8)	(24.3)	(18.3)	(16.3)	(81.6)
Switzerland	365.2***	355.3***	233.7***	372.9***	478.8***
	(24.5)	(27.1)	(23.9)	(24.7)	(60.1)
Constant	342.1***	322.1***	191.3***	315.7***	522.3***
	(15.8)	(28.4)	(8.1)	(11.0)	(29.0)

Table 5: Quantile Instrumental Variable Estimates

Independent variable: Lifetime income	Conditional		
	`qreg`	`ivqte` - AAI	`ivqreg` - ChH
Q8%	-23.7***	-28.1*	-132.3***
	(8.6)	(16.4)	(32.4)
Q10%	-22.3***	-29.8	-160.4***
	(7.4)	(19.2)	(30.6)
Q15%	-19.6***	-35.1**	-144.4***
	(7.3)	(15.2)	(27.1)
Q21%	-18.8***	-33.3**	-113.3***
	(6.4)	(16.2)	(24.7)
Q24%	-14.7**	-31.7	-91.3***
	(6.5)	(22.0)	(23.8)
Q29%	-8.9	-26.7	-61.6***
	(7.1)	(24.3)	(22.7)
Q35%	-4.0	-28.6	-53.2**
	(7.2)	(22.3)	(21.9)
Q40%	-2.4	-18.8	-44.3**
	(7.3)	(21.4)	(21.5)
Q41%	-2.3	-21.1	-52.3**
	(7.4)	(25.2)	(21.5)
Q50%	-2.1	-14.6	-14.7
	(9.2)	(25.3)	(21.1)
Q54%	8.3	-12.8	-22.9
	(10.1)	(33.6)	(21.2)
Q60%	14.8	-13.0	-19.8
	(9.8)	(28.0)	(21.3)
Q65%	17.5	-4.8	-29.1
	(11.4)	(34.3)	(21.6)
Q70%	14.7	-2.3	16.3
	(13.4)	(35.4)	(22.1)
Q75%	24.7*	13.0	55.6**
	(13.6)	(40.5)	(22.9)
Q80%	26.1	7.0	50.0**
	(16.1)	(49.8)	(24.1)
Q85%	35.7*	15.7	8.8
	(19.1)	(44.6)	(26.0)
Q90%	54.8*	22.7	26.0
	(31.2)	(61.2)	(30.1)
Q95%	95.7**	40.2	137.8***
	(43.6)	(86.7)	(43.1)

Continued on Next Page...

Table 5 – Continued

	`qreg`	`ivqte` - AAI	`ivqreg` - ChH
Controls (reported at Q50%)			
Austria	-51.4***	-59.6	-54.6*
	(17.2)	(64.7)	(32.8)
Belgium	-5.7	-24.8	-8.9
	(13.2)	(19.7)	(25.5)
Denmark	121.6***	130.3***	116.1***
	(15.9)	(29.7)	(27.9)
France	47.2***	52.6	41.7
	(16.1)	(66.7)	(26.8)
Italy	-87.9***	-98.7***	-94.5***
	(14.0)	(25.9)	(25.0)
Netherlands	9.1	-20.0	2.9
	(16.4)	(18.3)	(27.8)
Spain	-155.8***	-180.4***	-163.5***
	(18.3)	(21.0)	(30.1)
Sweden	77.2***	60.8**	77.5***
	(20.3)	(26.4)	(27.5)
Switzerland	372.9***	305.8***	374.3***
	(22.4)	(53.7)	(30.7)

Table 6: Quantile treatment effect in Regression Discontinuity design (part 1).

Lifetime	Austria		Sweden		Spain	
Income	ivqte-AAI	rddqte-FFM	ivqte-AAI	rddqte-FFM	ivqte-AAI	rddqte-FFM
Q5%	-179.7	-147.6	19.5	19.5	-26.9	-139.6
	(149.2)	(361.6)	(211.7)	(140.1)	(44.2)	(141.5)
Q10%	-167.1	-158.1	-4.4	19.5	-29.7	-132.1
	(208.7)	(349.4)	(216.8)	(140.8)	(37.3)	(107.0)
Q15%	-162.9	-161.2	24.1	-21.4	-36.7	-147.9**
	(162.6)	(342.5)	(205.1)	(102.4)	(48.2)	(69.8)
Q20%	-176.8	-121.9	21.3	-21.4	-57.7	-147.9**
	(108.0)	(330.2)	(229.8)	(102.8)	(52.5)	(64.6)
Q25%	-188.5	-134.1	41.4	-11.3	-75.1	-144.9**
	(186.6)	(315.0)	(272.5)	(123.7)	(61.9)	(62.4)
Q30%	-186.4	-154.0	11.2	-17.5	-71.9	-147.8**
	(243.5)	(299.6)	(274.9)	(127.8)	(66.9)	(58.9)
Q35%	-216.8	-170.7	33.0	0.0	-73.3	-151.5***
	(170.3)	(289.8)	(272.8)	(142.9)	(71.7)	(55.9)
Q40%	-253.2	-175.2	41.0	0.0	-112.5	-167.5***
	(333.6)	(284.0)	(408.4)	(143.7)	(86.6)	(51.6)
Q45%	-277.6	-179.0	48.1	-32.7	-125.1*	-181.9***
	(257.7)	(268.8)	(406.6)	(161.4)	(67.4)	(51.3)
Q50%	-297.5	-190.6	63.7	-32.7	-119.1	-169.0***
	(253.5)	(262.7)	(414.0)	(162.7)	(78.0)	(52.8)
Q55%	-369.8	-193.7	78.0	-29.1	-118.5	-177.6***
	(251.7)	(255.2)	(561.8)	(172.9)	(73.8)	(53.2)
Q60%	-371.3**	-228.1	102.3	-17.2	-131.9	-168.5***
	(150.9)	(264.7)	(584.4)	(239.4)	(106.9)	(57.9)
Q65%	-382.6	-310.5	159.1	-63.5	-149.3	-160.4**
	(292.6)	(414.3)	(624.6)	(340.6)	(101.0)	(72.9)
Q70%	-391.9	-395.9	223.0	-65.0	-155.1	-146.3**
	(373.8)	(707.9)	(819.7)	(415.6)	(156.3)	(71.9)
Q75%	-455.2	-551.8	186.2	-95.0	-211.4	-144.8*
	(368.3)	(568.5)	(822.9)	(382.0)	(160.7)	(74.3)
Q80%	-427.8**	-584.9	219.8	-118.5	-365.5*	-159.3**
	(195.0)	(498.2)	(839.8)	(459.5)	(198.9)	(80.0)
Q85%	-461.6	-640.7	271.5	-167.5	-360.2*	-166.6*
	(284.2)	(451.9)	(964.5)	(715.1)	(186.3)	(94.7)
Q90%	-518.6**	-929.3***	405.2	-257.0	-592.1***	-169.7
	(189.7)	(226.0)	(975.4)	(419.1)	(203.8)	(142.4)
Q95%	-578.3	-919.8***	573.3	-299.8	-618.9***	-308.0
	(515.9)	(205.1)	(1031.0)	(437.2)	(212.3)	(258.0)

Table 7: Quantile treatment effect in Regression Discontinuity design (part 2).

Lifetime	Italy		Denmark		Switzerland	
Income	ivqte-AAI	rddqte-FFM	ivqte-AAI	rddqte-FFM	ivqte-AAI	rddqte-FFM
Q5%	-221.3***	-273.4*	-10.6	122.6	-63.2	-389.6***
	(30.6)	(158.4)	(113.9)	(154.0)	(98.6)	(87.0)
Q10%	-240.1**	-277.4*	46.2	82.4	-103.8	-394.8***
	(111.1)	(142.9)	(127.4)	(144.9)	(77.1)	(72.7)
Q15%	-226.2***	-291.0**	31.2	62.9	-110.8	-369.8***
	(75.3)	(113.6)	(131.1)	(148.2)	(86.9)	(56.0)
Q20%	-235.7***	-307.6***	27.4	36.3	-182.1*	-359.1***
	(83.5)	(99.6)	(106.5)	(150.7)	(94.5)	(58.0)
Q25%	-237.2***	-290.0***	43.5	33.9	-162.9**	-325.4***
	(63.2)	(97.5)	(97.1)	(150.9)	(81.0)	(65.8)
Q30%	-251.4***	-290.0***	55.0	13.0	-172.4*	-334.4***
	(88.4)	(98.0)	(98.3)	(150.7)	(93.1)	(67.9)
Q35%	-248.2**	-281.8***	69.6	20.7	-219.3**	-308.1***
	(120.4)	(100.5)	(110.3)	(149.9)	(94.3)	(71.9)
Q40%	-255.9	-271.9**	80.8	44.7	-223.9***	-310.0***
	(155.7)	(107.7)	(116.8)	(150.9)	(73.9)	(78.7)
Q45%	-259.8***	-247.4**	87.3	50.3	-196.3**	-315.9***
	(43.8)	(105.6)	(149.5)	(155.8)	(88.0)	(81.2)
Q50%	-281.6**	-253.3**	79.6	39.5	-164.6*	-316.8***
	(122.6)	(110.2)	(150.1)	(168.8)	(91.6)	(88.9)
Q55%	-294.2***	-266.9**	72.0	2.9	-167.4*	-320.8***
	(42.2)	(118.6)	(129.0)	(181.8)	(90.6)	(91.1)
Q60%	-311.4**	-266.9**	119.0	30.5	-158.3	-334.3***
	(129.5)	(118.5)	(148.2)	(210.0)	(110.1)	(97.7)
Q65%	-305.2***	-312.6*	128.2	0.0	-174.3	-305.6***
	(32.2)	(188.1)	(152.0)	(313.0)	(144.0)	(108.6)
Q70%	-309.7**	-332.8***	134.3	46.3	-158.1	-191.3
	(131.4)	(126.3)	(193.8)	(566.9)	(102.7)	(301.0)
Q75%	-334.5***	-301.2**	91.3	118.6	-212.2*	-70.9
	(81.4)	(145.9)	(232.2)	(649.7)	(125.2)	(342.6)
Q80%	-323.7***	-320.4**	185.1	198.8	-201.1	12.7
	(89.8)	(138.4)	(220.5)	(532.7)	(212.0)	(315.9)
Q85%	-359.1***	-294.2**	180.6	236.6	-180.0	85.0
	(99.7)	(124.8)	(288.8)	(409.3)	(184.2)	(287.2)
Q90%	-453.7**	-351.7**	251.5	358.6	-195.4	92.9
	(209.6)	(157.6)	(298.0)	(334.1)	(316.5)	(233.6)
Q95%	-408.1	-339.1**	370.0	374.5	-394.0	113.5
	(258.1)	(167.8)	(355.6)	(245.1)	(337.4)	(178.2)

Table 8: Robustness checks. Regressions run separately by quintiles.

Independent variable: Lifetime Income	OLS	2SLS	QR(.50)
Quintile 1	-11.4***	-43.3*	-13.5**
	(4.1)	(23.8)	(6.5)
Quintile 2	-5.1**	-27.6**	-9.0**
	(2.5)	(11.7)	(3.7)
Quintile 3	0.3	-13.5	0.9
	(2.5)	(13.0)	(3.1)
Quintile 4	3.6	25.0	0.0
	(4.4)	(20.9)	(6.1)
Quintile 4	22.3	124.2	24.2
	(33.6)	(121.9)	(29.7)

Table 9: Robustness checks. Regressions with continuous treatment.

Independent variable:	Quantile regression	
Lifetime Income	QREG	ChH
Q10%	-3.7***	-13.0***
	(0.8)	(1.4)
Q20%	-2.4***	-17.3***
	(0.7)	(1.2)
Q30%	-1.7*	-19.7***
	(0.9)	(1.1)
Q40%	-1.0	-22.0***
	(0.7)	(1.1)
Q50%	-1.3	-18.8***
	(1.0)	(1.0)
Q60%	0.8	-14.6***
	(1.2)	(1.0)
Q70%	0.7	-10.5***
	(1.7)	(1.0)
Q80%	1.8	-6.8***
	(1.5)	(1.1)
Q90%	0.4	1.8
	(3.0)	(1.4)

Figure 1: Kernel density estimates of lifetime income for retired by and after age 62.

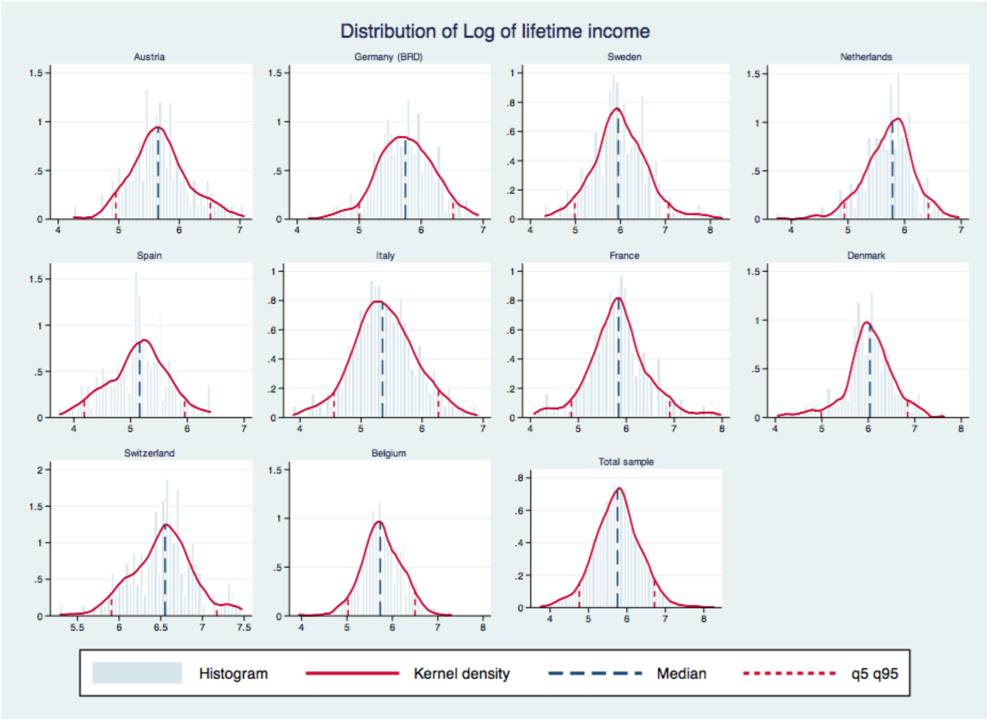


Figure 2: Kernel density estimates of lifetime income for retired by and after age 62.

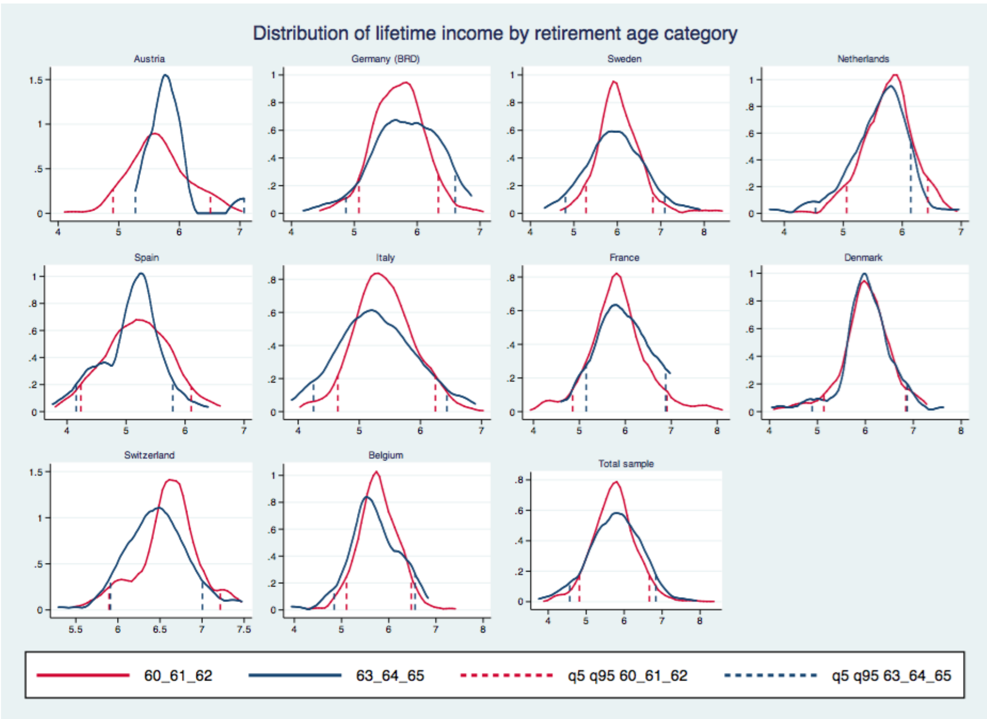


Figure 3: Ordinary Least Squares Estimates vs. Quantile Regression.

Figure 4: Quantile Regression vs. Quantile Treatment Effect (AAI).

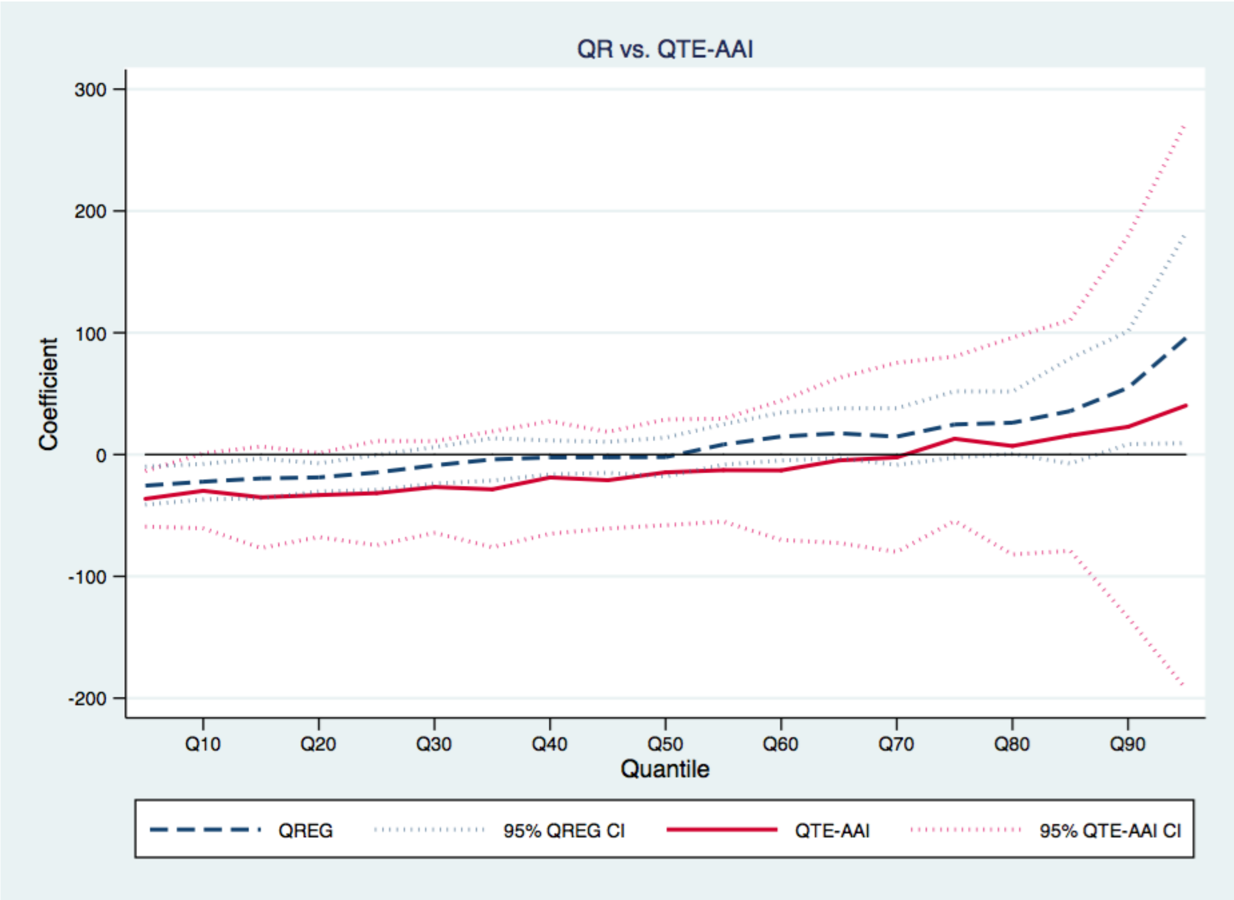


Figure 5: Quantile Treatment effect by the two estimators QTE-AAI and QIV-ChH.

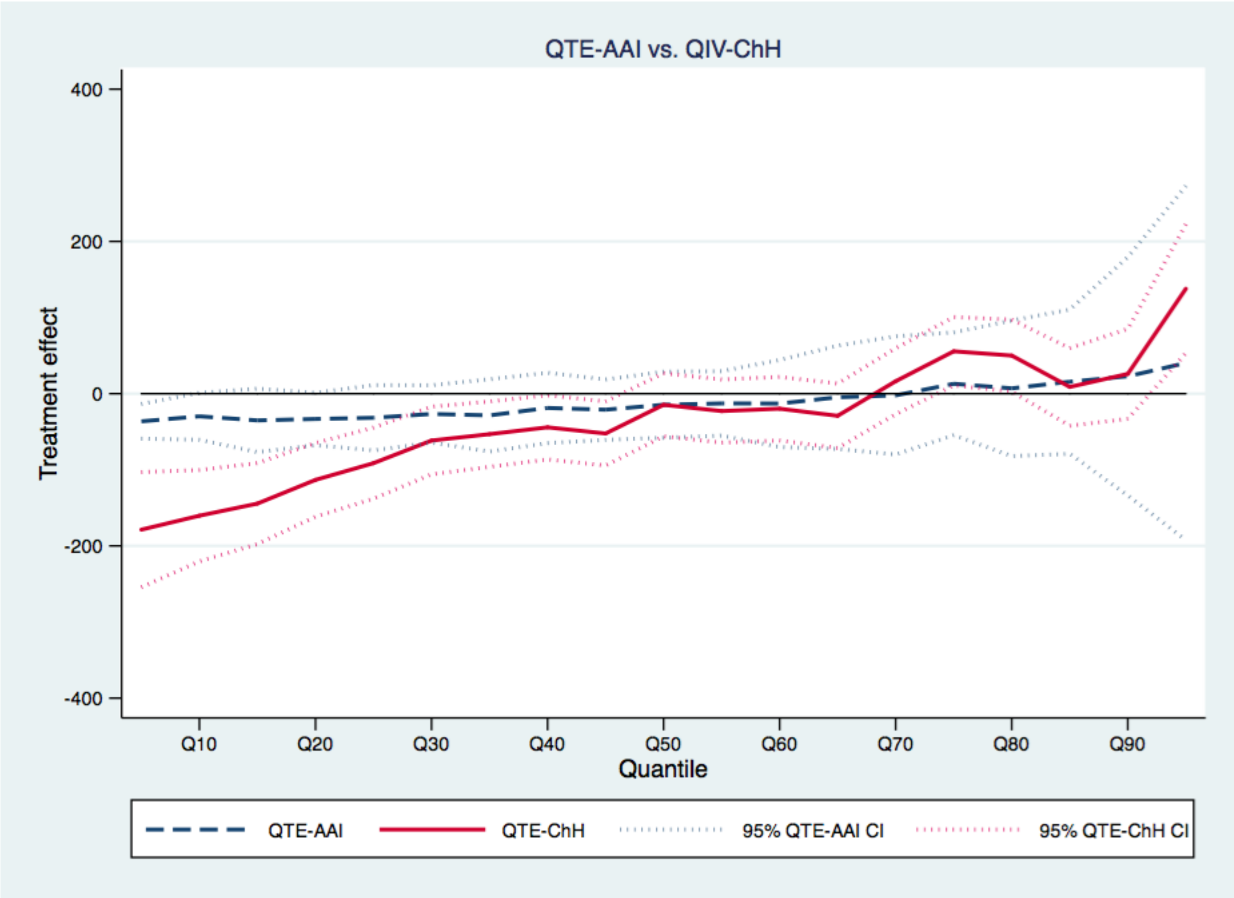


Figure 6: Quantile Treatment effect of retirement on lifetime income by country in a regression discontinuity design.

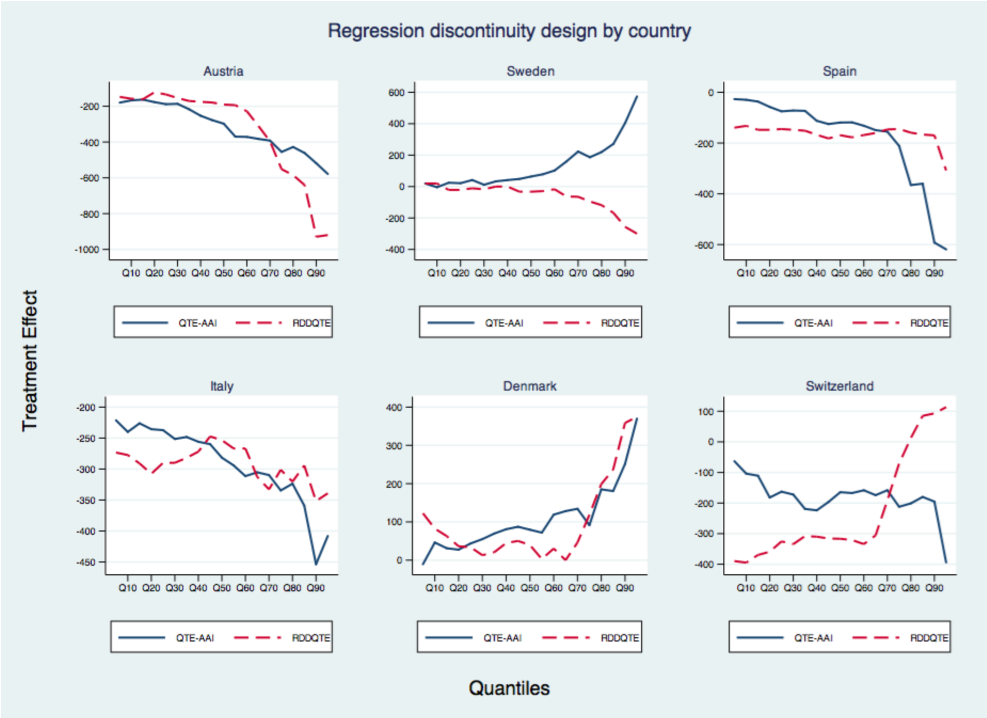
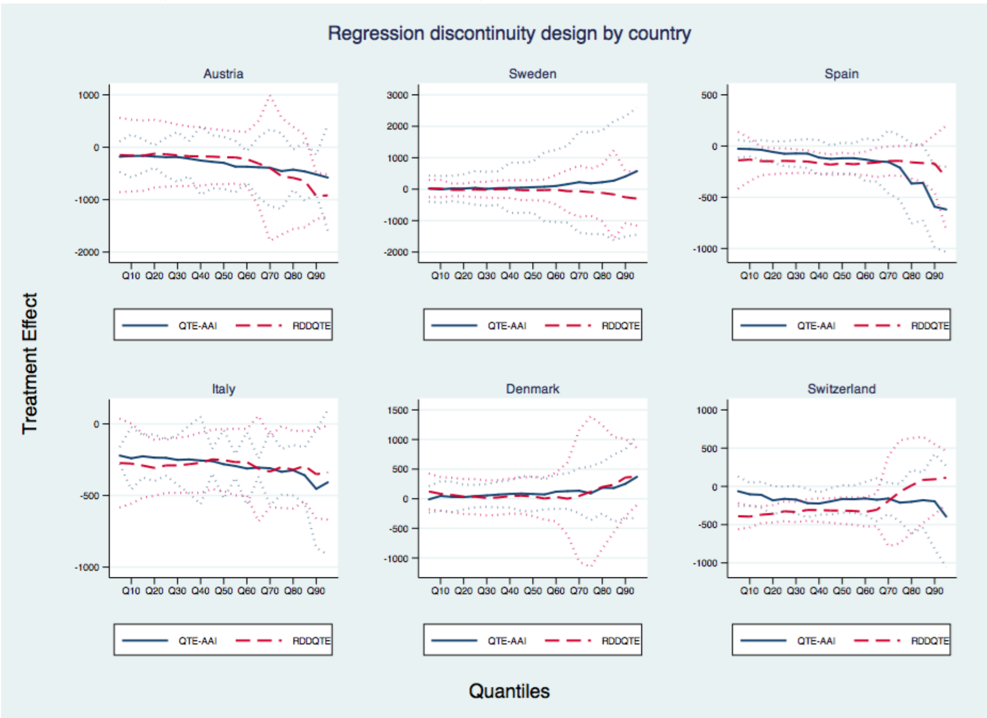


Figure 7: Quantile Treatment effect of retirement on lifetime income by country in a regression discontinuity design (with confidence intervals).



A Legal normal and early retirement ages

Table 10: Normal retirement ages for males:

Year	AT	DE	SE	NL	ES	IT	FR	DK	GR	CH	BE	CZ	PL	IR
1967	65	65	67	65	65	60	65	67	65	65	65	60	65	70
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
1973	65	65	67	65	65	60	65	67	65	65	65	60	65	70
1974	65	65	67	65	65	60	65	67	65	65	65	60	65	**69**
1975	65	65	67	65	65	60	65	67	65	65	65	60	65	**68**
1976	65	65	**65**	65	65	60	65	67	65	65	65	60	65	68
1977	65	65	65	65	65	60	65	67	65	65	65	60	65	**67**
1978	65	65	65	65	65	60	65	67	65	65	65	60	65	67
1979	65	65	65	65	65	60	65	67	65	65	65	60	65	**66**
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
1982	65	65	65	65	65	60	65	67	65	65	65	60	65	66
1983	65	65	65	65	65	60	**60**	67	65	65	65	60	65	66
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
1994	65	65	65	65	65	60	60	67	65	65	65	60	65	66
1995	65	65	65	65	65	**61**	60	67	65	65	65	60	65	66
1996	65	65	65	65	65	**62**	60	67	65	65	65	**60.16**	65	66
1997	65	65	65	65	65	**63**	60	67	65	65	65	**60.33**	65	66
1998	65	65	65	65	65	**63**	60	67	65	65	65	**60.5**	65	66
1999	65	65	65	65	65	**64**	60	67	65	65	65	**60.67**	65	66
2000	65	65	65	65	65	**65**	60	67	65	65	65	**60.83**	65	66
2001	65	65	65	65	65	65	60	67	65	65	65	**61**	65	66
2002	65	65	65	65	65	65	60	67	65	65	65	**61.16**	65	66
2003	65	65	65	65	65	65	60	67	65	65	65	**61.33**	65	66
2004	65	65	65	65	65	65	60	**65**	65	65	65	**61.5**	65	66
2005	65	65	65	65	65	65	60	65	65	65	65	**61.67**	65	66
2006	65	65	65	65	65	65	60	65	65	65	65	**61.83**	65	66
2007	65	65	65	65	65	65	60	65	65	65	65	**62**	65	66

Table 11: Early retirement ages for males:

Year	AT	DE	SE	NL	ES	IT	FR	DK	GR	CH	BE	CZ	PL
1967	60	65	63	65	60	55	65	67	65	65	60	60	60
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
1971	60	65	63	65	60	55	65	67	65	65	60	60	60
1972	60	**63**	63	65	60	55	**60**	67	65	65	60	60	60
1973	60	63	63	65	60	55	60	67	65	65	60	60	60
1974	60	63	63	65	60	55	60	67	65	65	60	60	60
1975	60	63	63	65	60	55	60	67	65	65	60	60	60
1976	60	63	**60**	**63**	60	55	60	67	65	65	60	60	60
1977	60	63	60	63	60	55	60	67	65	65	60	60	60
1978	60	63	60	63	60	55	60	67	65	65	60	60	60
1979	60	63	60	63	60	55	60	**60**	65	65	60	60	60
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
1982	60	63	60	58	60	55	**55**	60	65	65	60	60	60
1983	60	63	60	58	60	55	55	60	65	65	60	60	60
1984	60	63	60	58	60	55	**60**	60	65	65	60	60	60
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
1992	60	63	60	58	60	55	60	55	65	65	60	60	60
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
1995	60	63	60	58	60	**57**	60	50	65	65	60	60	60
1996	60	63	60	58	60	57	60	60	65	65	60	**60.16**	60
1997	60	63	60	55+	60	57	60	60	65	**64**	60	**60.33**	60
1998	60	63	**61**	55+	60	57	60	60	65	64	60	**60.5**	60
1999	60	63	61	55+	60	57	60	60	65	64	60	**60.67**	60
2000	60	63	61	55+	60	57	60	60	65	64	60	**60.83**	60
2001	60	63	61	55+	60	57	60	60	65	**63**	60	**61**	60
2002	60	63	61	55+	**61**	57	60	60	65	63	60	**61.16**	60
2003	**61**	65	61	55+	61	57	60	60	65	65	60	**61.33**	60
2004	61	63	61	55+	61	57	60	60	65	63	60	**61.5**	60
2005	61	63	61	55+	61	57	60	60	65	63	60	**61.67**	60
2006	**62**	63	61	55+	61	57	60	60	65	63	60	**61.83**	60
2007	62	63	61	55+	61	57	60	60	65	63	60	**62**	60
2008	62	63	61	55+	61	57	60	60	65	63	60	**62**	60
2009	62	63	61	55+	61	57	60	60	65	63	60	**62**	60