UCLouvain
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Heterogeneity in pension policy

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"The problem of the nature and extent of the provision to be made for old age is the most important, and in some ways the most difficult, of all the problems of social security."

The Beveridge Report,
November 1942

Acknowledgements

You have in your hands one of the most awkward items in the world. It is an economic Ph.D. thesis about pensions written by a cook. Let me explain how this particular thing happened and, by the way, thank all the people that made it possible.

I was born the 9^{th} *of February 1993 in Montigny-le-Tilleul. Aged 13, I decided to study cooking at Ecole Hôtelière Provinciale de Namur. I thank my parents and family for their support during all my studies and for always supporting (and accepting) my educational choices. I really liked those studies and some of the teachers still have an impact on my way of working. I thank Jean-Louis Choquet and Raoul Francart for their teaching. I also thank Michèle Dutz for her support during those studies. At the end of those four years, I decided to go on with a Bachelor in Hotel Management. I discovered a different way of teaching - more theoretical and less practical. I thank particularly two teachers, Emmanuel Didion and Cédric Vandervaeren, for the quality of their lessons and all the discussions that we had (and still have). At the end of those three years, I wanted to know more about economics. My Hotel Management Bachelor was really good, but I thought that some extra knowledge about economics could have been quite useful. I decided to start a Bachelor in Management and Economics at Université de Namur. It was a real challenge. At the time I took this decision, I had a really poor background in mathematics. There were only three hours of mathematics in my cooking studies during the first two years and not at all in the last two. I was told that it was reckless for me to start a Bachelor in Management and Economics. I was stubborn enough to try and learned (almost) everything on YouTube during the summer holidays. I thank Eddy Corbisier (my volunteer mathematics teacher) who helped me when I had trouble understanding the last details of some exercises.*

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Introduction

Population ageing will be one of the most important challenges in the next decades. According to the Comité d'Etude sur le Vieillissement (2021), the economic dependency ratio (i.e. the ratio of retirees to workers) will increase by 35 % between 2020 and 2070 in Belgium. It is not only a particularity of Belgium, but of all advanced economies (OECD, 2019). Population ageing will *deeply* change our societies. We will need to take care of more dependent people. We will have to pay more pensions. The relative prices will change as the ratio of old/young people with their particular consumption baskets will change. The interest rate will change as old and young have different saving/spending rates. Many challenges lie ahead. As population ageing has never happened before, we need many scientific studies to try to forecast and anticipate its consequences. This Ph.D. thesis focuses on the issue of pensions, which is one of the most noticeable domains. Although pensions are not the only issue linked to population ageing, it is one of the most discussed. As the ratio of retirees/workers will increase, pension systems will have to be adapted. The economics of pensions probably starts with the seminal work of Samuelson (1958) and has expanded in various directions. This thesis builds on the literature on heterogeneity in pension policy. Chapter 1 delves into the analysis of heterogeneity in pension policy regarding the age of the individuals at the time of the reform. Chapter 2 analyses the possibility to account for the heterogeneity of careers, in particular in terms of arduousness, when designing pension schemes. Chapter 3 explores the implications for pension policy of the heterogeneity of people regarding their life expectancies and their lifespans.[1]

In Chapter 1 (co-authored with Jean Hindriks), we analyse the distributional consequences of policies aimed at balancing the pension system in case of an increase in the economic dependency ratio. Three options exist: increasing the contribution rate, decreasing pension benefits or raising the retirement age. Without loss of generality, we focus our analysis on the second option. In this chapter, heterogeneity corresponds to the differences

[1]The life expectancy is the number of years someone can expect to live, the lifespan is the number of years he "actually" lives.

in terms of the individuals' age at the time of the reform. We assess the heterogeneous impact of decreasing the *aggregate* level of pension benefits on the different cohorts. The difference between this chapter and the literature is that we analyse the problem of balancing the pension system over a finite horizon, whereas the literature (e.g. Auerbach et al., 1994) often uses an infinite horizon. We also use the individual remaining lifetime, whereas the literature often uses the full lifecycle. Decreasing the overall level of benefits could be done by decreasing the accrual or the indexation rate. The accrual rate is the one at which the right to pension benefit builds up during the contributory phase. Whereas the indexation rate is the one at which accrued pension rights are indexed (to account for inflation of GDP growth for instance), both during the working and the retirement periods. We show that these two instruments are not equivalent regarding their distributional consequences. Decreasing the accrual rate hurts only the future retirees while decreasing the indexation rate helps shift part of the costs to the current generations of pensioners, thus achieving a more even distribution of the costs of balancing the pension system's finances. Using Belgian population and employment rates forecasts made by the Bureau Fédéral du Plan for the period 2020-2070, we show that the youngest half of the population bears 85 % of the costs of an accrual reform, while it is 65 % for an indexation reform. Thus, a planner would favour lowering the indexation rate. However, the outcome of a democratic (majority-rule based) vote would be to go for the (lower) accrual rate. This is simply because old voters represent a (too) larger share of the population. Then, we quantify the impact of these two reform options in terms of their relative inequalities, using the no-reform case as a reference. We use the Gini index of the relative pension loss as an indicator of inequality. We show that options that smooth the costs of the reform among the members of the society fail to win majority.

In Chapter 2 (co-authored with Sandy Tubeuf and Vincent Vandenberghe), we analyse the heterogeneity of careers in terms of arduousness. Some jobs are evidently more arduous than others, leading some economists (e.g. Zaidi and Whitehouse, 2009) to say that retirement policy should compensate individuals who experienced more arduous jobs. One of the problems with the implementation of this policy is the non-existence of a readily available indicator of job arduousness. Using the 7$^{\text{th}}$ wave of the Survey on Health, Retirement and Ageing in Europe, we show the possibility to infer a ranking of job arduousness from the health of individuals at old age. More manual and physically intense jobs (like "Refuse and other elementary workers") are more harmful for late-life health than jobs less physical (like "Teaching professionals"). We try to overcome the problem of endogeneity in the choice of occupation by using various specifications for our occupation variable. We use the first, main, last job or the time spent in each job and show that our results are robust. Another strength of the paper is the use of pre-labour entry control variables, like educational attainment, parental longevity or childhood health. Using coefficients decomposition methods (Gelbach, 2016), we show that pre-labour entry control variables correlate with the chosen occupation and thus that their incorporations in the econometric model are important to properly assess the net contribution of occupation to late-life health. The chapter contains two extensions. First, we estimate the difference of career length it would take to equalise the expected health at the moment of retirement across occupations; by dividing the above-estimated net contribution of occupation to late-life health by some estimate of the impact of one year of age on the decline of health around typical retirement ages. The results of the above estimations suggest that it would be quite considerable (in the range of 15 years between the most vs. least arduous occupation). This stresses the difficulty to account for heterogeneity in pension policy. In a second extension, we try to assess the overall relative importance of occupation to late-life health, using variance decomposition methods (Shorrocks, 1982). We decompose the variance of health across different components - occupation, education, age, childhood conditions, country and father's occupation. We show that occupation, although a significant contributor of bad health beyond the age of 50, is not its main driver. Childhood/pre-labour conditions are more important. This suggests that policies aimed at equalising late-life opportunities should also target the early years of life, and not exclusively rest on pension/retirement schemes.

In the last chapter, we consider the problem of using life expectancy of individuals to predict their lifespans. Many studies (e.g. Meara et al., 2008) have shown the existence of a socioeconomic life expectancy gradient. Low socioeconomic status people can expect to live less time than high socioeconomic status people. This explains why many economists (see e.g. Ayuso et al., 2017) have called for differentiation of retirement age to compensate for socioeconomic status driven life expectancy differences, in particular when policy-makers are raising the retirement age to cope with population ageing. If what matters from a normative point of view is the lifespan of each individual, we argue that this policy recommendation is only relevant if the life expectancy provides a very accurate information about the lifespan of an individual. In this chapter, we use the US mortality rates from Chetty et al. (2016) to analyse the relevance of using the life expectancy by socioeconomic status for pension policy. We build a gap index to measure the information brought by life expectancy and show that this indicator brings relatively limited information. This is due to two facts. First, the distribution of lifespan is huge inside each socioeconomic status. Second, the distributions of lifespan across socioeconomic status tend to overlap to a great extent. Therefore, using a summary indicator like life expectancy for pension policy does a poor job when it comes to matching the full distribution of lifespans. Someone with a high life expectancy could die young and someone with a low life expectancy could die old.

Chapter 1

Intergenerational consequences of gradual pension reforms

Co-author: Jean Hindriks
Forthcoming in the European Journal of Political Economy

Balancing the government budget in an ageing economy may require adjusting gradually pension benefits. Such policy change can take two forms: adjusting the accrual rate (the rate at which individuals built-up pension entitlements while working) or the indexation rate (the rate at which accrued entitlements are linked to nominal wage growth). We compare the (actuarial) consequences of such gradual policies across cohorts. We identify a fundamental generational tradeoff between democracy and equality, defined as the same relative pension loss across generations. In particular, we show that for Belgium in 2020, 80% of the voting population alive at the time of the reform prefers the accrual to the indexation reform, with the implication that the youngest half of the population would bear 85% of the total adjustment cost. The indexation reform provides more generational equality because the phasing in over time has a larger base and, thus, benefit cut can be smaller per capita. We then consider other reforms improving the generational equality, showing that all those reforms fail to gain majority support. We consider labour incentives and show how the accrual and indexation rates have different effects on the employment rates. Finally, we show that our results are robust to altruistic voting for the next generation.

1.1 Introduction

Many public pension schemes around the world involve pay-as-you-go schemes. These are sustainable if the contributions from the workers cover the pension benefits of the retirees.

For pay-as-you-go schemes to avoid running a structural deficit, it has to ensure that the revenue flowing into the scheme from current contributors covers the expenditure required for the payment of benefits to current retirees. The current retirement of the baby boom generations increases the ratio of current beneficiaries to current contributors, making pay-as-you-go schemes unsustainable. European countries have to undertake ambitious reforms and these should not only look at sustainability, but also at intergenerational consequences (European Commission, 2021). Our objective in this chapter is to study in a transparent way the prospective (actuarial) consequences of pension reforms in terms of (relative) pension loss. Our goal is not only to analyse it for current retirees or near-retirees cohorts, but for all generations alive at the time of the reform. By doing so, we avoid the mistake that consists in ignoring the pension burden adjustment for future generations.

The literature on reforming pay-as-you-go pension comprises several strands. A first strand examines the radical choice of switching from pay-as-you-go scheme (unfunded) to funded pension schemes (Kotlikoff and Burns, 2004). The drawback of this option is the high cost borne by the transitional generations who have to finance the two schemes at the same time (Miles, 1998). The second strand of the literature considers that there are three possible options to gradually assure the sustainability of pay-as-you-go schemes: adapting the contribution rate, changing the pension benefit or adjusting the retirement age. That literature often puts the focus on the choice (and the optimal mix) of those three options, without carefully analysing the age and cohort-specific consequences of those pension policies. In this chapter, we follow the microsimulation approach to compare different benefit adjustments (Blanchet et al., 2016). Benefit adjustment can be cohort-specific (a cohort with longer remaining lifespan receives lower benefits than a cohort with shorter remaining lifespan), or time-specific (changing indexation rule by simply reducing benefits over time relative to average earnings). A key difference between these two alternatives for adjusting benefits is that the cohort-specific rule only applies the adjustment to the newly retiring cohort, whereas the time-specific rule reduces initial benefits for the newly retiring as well as for the already retired. So, phasing in benefit cuts over time has a larger base and, thus, benefit cuts can be smaller per capita. Different cohorts will have different preferences over the cohort-specific reform and the time-specific reform.[1] A third strand of the literature, to which this chapter also relates, considers the problem of heterogeneity. Bi and Zubairy (2022) show that the heterogeneity in the phase-in period is important for making pension

[1] Bozio et al. (2019) compare the adjustment of a (point) pension system to economic and demographic shocks using different forms of indexation. However, they do not look at the heterogeneity of the impact on the different cohorts, as well as the political preferences for those reforms among the different cohorts.

reform. They show that near-retirees individuals could decide to retire sooner depending on the phase-in design.[2]

The focus of our chapter is on the intergenerational inequality of different pension reforms aimed at securing financial sustainability. A reform R is more equal than a reform R' if the inequality of the relative pension loss is lower. The inequality is measured by the Gini index of the relative pension loss. The relative pension loss is defined as the percentage of the expected pension wealth that is forgone as a result of the reform. Hence, our normative criterion is to equalise relative pension loss.[3] In doing so, we will focus on alternative gradual benefit adjustments via a reduction of the accrual or the indexation rate, assuming a fixed contribution rate. The main reason for not considering the possibility to raise contributions is their well-documented harmful consequences on long-run employment, growth and welfare (e.g. Kotlikoff et al., 2007; Kitao, 2014). Another focus of our chapter is the political support for the different pension reforms. Most pension systems rely on a contract between different generations, and such intergenerational agreements cannot be dissolved. The path dependence is structural. The past pension rights and promises already accumulated from entitlements put a stop to the more radical proposals. So, we will focus on gradual reforms and we will impose the grandfather clause (no retrospective reform) so that reform can only affect future pension rights. The grandfather clause in pension reforms refers to the protection of the transitional generations, by grandfathering some of the implicit pension rights in the old system so that we have a gradual phase in of the new system. With slight abuse of language, we will refer to the grandfather clause as the exemption of past pension rights from the reform. In concrete terms, we mean by grandfathering that past pension rights are separated from future pension rights. Interestingly, the political support for any reform is itself influenced by the ageing process. Reforms that increase the retirement age can be politically accepted when few people are near retirement age, but impossible with a growing size of the cohorts close to retirement (Bütler, 2000; Bello and Galasso, 2020). Retirement age reforms are more tricky to assess because their effects on labour force participation is ambiguous. Li (2018) showed that increasing the normal retirement age causes a decrease of payroll tax revenue and an increase in disability insurance expenses offsetting about 40% of

[2] Laun et al. (2019) and Devriendt et al. (2022) analyse the heterogeneity of the impact of pension reforms for different income groups (within cohort heterogeneity) using OLG model with heterogeneous income abilities. To reduce intra-generational inequality, Devriendt et al. (2022) show that increasing retirement age reform should be combined with more progressivity of the link between earnings and benefits.

[3] Our analysis of pension reform is not retrospective. We only consider the prospective consequences of pension reform without considering past income levels, pension benefits and contributions. In doing so, we do not consider conditioning pension loss to each cohort lifetime income. Richer cohorts could face higher pension loss than poorer cohorts. This issue is left for future work.

the decrease of pension expenses. In this chapter, we will not consider reforms that increase the retirement age. Cremer and Pestieau (2000) argue that pension reforms are shaped by conflicting political forces. The retirees are willing to shift the cost on the workers, but they need those workers to pay their pensions (Breyer and Stolte, 2001). With population ageing the median voter gets older, and the old people get politically more powerful (Sinn and Uebelmesser, 2003). There are empirical evidences that countries have not treated cohorts equitably in their pension reforms, namely reducing the entitlement for younger generations while sparing those near retirement (Börsch-Supan, 2013; Fouejieu et al., 2021). One particular exception is Sweden, which was able to implement its reform because, at that time, they were more winners than losers from it (Selén and Ståhlberg, 2007).

In this chapter, we compare the prospective consequences for all generations alive at the time of the reform adjusting gradually pension benefits. To assess the generational balance of the different reforms, we will have to adopt a criterion of generational equality. We will consider the inequality across cohorts of the pension loss (relative to no reform) when gradually adjusting the pension benefit to balance the government budget in the long run (finite horizon).[4] To adjust the pension benefit, two parameters are available: the accrual and the indexation rates. Those are key parameters in most pension systems (either defined benefit, point system or notional defined contribution). The accrual rate is the one at which someone builds up his rights to pension benefits, while the indexation rate guarantees that accrued benefits (during both the work and retirement years) stay in line with wage growth in the economy. Those pension parameters are widely used around the world.[5] Various papers analyse the budgetary consequences of indexing relative to wages or to prices (Blanchet et al., 2016) and the pre- and post-retirement indexations (Piggott et al., 2009; Whitehouse, 2009). Indexing partially erodes pensions over time and can put older retirees at risk of poverty (Hohnerlein, 2019). We contribute to this literature by analysing the heterogeneity of the impact on the different cohorts alive at the time of the reform. The closest paper to ours is Auerbach and Lee (2011), which analyses the heterogeneity of the impact of pension reforms on different cohorts. However, their framework is different from ours. They base their analysis on the whole lifetime of individuals (both retrospectively and prospectively) and do not study the political acceptability of the reforms. On the contrary, considering

[4] Preserving the generational balance is of particular importance for new reforms because Chen et al. (2018) have shown that the young and the working individuals bear most of the costs of previous crises. Barr and Diamond (2008) and Kohli and Arza (2011) argue that reforms should aim to strike a balance between fiscal sustainability and generational balance.

[5] For instance, Poland indexes accrued pensions with respect to the inflation rate plus a fifth of the wage growth. In France, pensions are indexed relative to the wage growth minus the growth of the ratio of retirees to contributors (sustainability factor).

that pension reforms are generally not retroactive, we study the prospective effects of the reforms over the remaining lifetime of the generations currently alive. If we would like to study the effect of the reform over the entire lifespan, we should limit our analysis to the cohorts not yet born; which is at odds with our objective to compare the political support for various reforms (Auerbach et al., 1994; Kotlikoff, 2003).[6] In a nutshell, the pension reform affects pension benefits, and so computing the expected changes of those benefits to balance the intertemporal budget is an effective way of measuring the reform's effect for different generations. The analysis of the distributional consequences of the reform is a necessary preliminary step to any welfare analysis of it. The reform is evaluated on a single dimension which is cohort-age. In doing so, we ignore within cohort heterogeneity in terms of income and needs. Extending the model in that direction would require additional within cohort distribution analysis of pension reforms, but this would not change our main findings on the distributive analysis between cohorts. We also consider the employment response to the pension reforms.[7] The assumption is that the reform will change the employment rates of different cohorts, proportionally to their pension loss and the employment elasticity.[8] Given those assumptions, we calculate the expected reduction of pension benefits needed to balance the intertemporal budget in the presence of employment response and compare the accrual and the indexation reforms. Lastly, we consider altruistic voting in which voters exhibit altruism towards future generations.

This chapter proceeds as follows. Section 1.2 presents the model. Section 1.3 illustrates the issues with a simple example. Section 1.4 describes the economic and demographic data used in our simulations of various pension reforms. We provide the prospective evaluation of accrual and indexation reforms in Section 1.5. Section 1.6 considers alternative pension reforms that improve generational equality. Section 1.7 considers longevity inequality, employment effects of pension reforms and intergenerational altruism. Section 1.8 concludes with some comments.

[6]Our approach has two key differences with generational accounting. First, instead of calculating the implicit tax burden from existing fiscal policy on generations not yet born given existing policy, we measure the unequal consequences of various pension reforms for the generations already born over their remaining lifetime. Second, we assess the impact of the pension reforms relative to the status quo over a finite horizon, instead of taking proper account of all age-related social transfers as in the generational accounting to compute the discounted lifetime net tax payment over infinite horizon (Banks et al., 1999).

[7]French et al. (2022), using regression discontinuity of cohort-specific pension reform in Poland, find changes in labour supply involving employment elasticity with respect to the net return to work (including expected pension benefits) of 0.44.

[8]We consider the aggregate elasticity averaging individual behavioural responses across individuals with heterogeneous preferences over income and leisure (some workers are willing to trade off lower pension for longer pension and other workers are not).

1.2 The model

At time t, the set of working age cohorts s is denoted W_t and the set of retired cohorts (still alive) is denoted R_t. The size of each cohort s in time t is N_t^s. Cohort size evolves over time as:

$$N_t^s = (1 - \mu_t^s) N_{t-1}^s \tag{1.1}$$

where μ_t^s is the mortality rate of cohort s in time t. Total employment is:

$$N_t^E = \sum_{s \in W_t} e_t^s N_t^s \tag{1.2}$$

where $e_t^s \in [0,1]$ is the employment rate of cohort $s \in W_t$ in time t, so the employment rate evolves over time and across cohorts. The total retired population is:

$$N_t^R = \sum_{s \in R_t} N_t^s \tag{1.3}$$

The dependency ratio in time t is:

$$D_t = \frac{N_t^R}{N_t^E} \tag{1.4}$$

Before retirement, for each working age cohort $s \in W_t$, the pension entitlement in time t, P_t^s, is the pension entitlement of time $t-1$ indexed at rate r_t^0 to the (nominal) wage growth, plus the pension entitlement earned in time t according to the accrual rate a_t.

$$P_t^s = P_{t-1}^s r_t^0 \frac{w_t}{w_{t-1}} + a_t w_t \tag{1.5}$$

After retirement, for each retired cohort s, pension benefit at time t is the pension benefit in $t-1$ indexed at rate r_t^1 to the (nominal) wage growth. In case of partial indexation of pensions on wage growth $r_t^1 < 1$, the replacement rates decrease with age. Note that the indexation rate may differ before and after retirement (e.g. dual indexation).

$$P_t^s = P_{t-1}^s r_t^1 \frac{w_t}{w_{t-1}} \tag{1.6}$$

We define the replacement rate ρ_t^s of the retired cohort $s \in R_t$ in time t as:

$$\rho_t^s = \frac{P_t^s}{w_t} \tag{1.7}$$

Note the difference between the *replacement rate* and the *benefit ratio*. The benefit ratio measures the average replacement rates among the retired population. At time t, the benefit ratio is:

$$\beta_t = \sum_{s \in R_t} \rho_t^s \frac{N_t^s}{N_t^R} \tag{1.8}$$

The short-term cash flow budget balance in time t is given by:

$$\beta_t D_t = \tau_t \tag{1.9}$$

where τ_t is the contribution rate. We adopt a long-term budget balance perspective. This means that the pension system should be in equilibrium on average over the period 2020-2100. We simulate a one-off permanent change in year 2020 in either the accrual or the indexation rate to balance the pension system over the period 2020-2100. We initially assume equal indexation pre- and post-retirement $r_t^0 = r_t^1 = r_t$ (we relax this assumption later). The pension parameters are initially set at (a_0, r_0) and, depending on the reform, change to a_1 or r_1. We set r_0 to 1 (i.e. full indexation to the wage growth) and a_0 to achieve budget balance in 2019. We then consider either a permanent accrual cut ($a_1 < a_0$) or a permanent indexation cut ($r_1 < r_0$) to balance the long-term budget constraint. All future pension spendings must be equal to all future pension contributions (fixing contribution rate $\tau_t = \tau_0$, $\forall t$).

$$\sum_{t=2020}^{2100} \sum_{s \in W_t} \tau_t w_t e_t^s N_t^s = \sum_{t=2020}^{2100} \sum_{s \in R_t} P_t^s(a_1, r_0) N_t^s = \sum_{t=2020}^{2100} \sum_{s \in R_t} P_t^s(a_0, r_1) N_t^s \tag{1.10}$$

Our budget approach is twofold. First, it is based on the intertemporal budget balance and not on short-term cash balance.[9] This enables the reform to be gradually phased in. One reason for gradual implementation is to avoid large differences of benefits between new retirees from one year to the next. We disregard short-term year-to-year adjustments not only to avoid the curse of dimensionality, but also to provide security of how the pension benefits will evolve in the mid/long run. Second, our budget approach is based on the principle of no perpetual deficit financing.

[9] Pension reforms must take long-run revenues and expenditures into consideration and not depend upon perpetual, long-term, deficit financing at the expense of future unborn taxpayers. The problem with the cash balance approach is that it does not take into account that pension policy today will change pension commitments in the future and such budget impact ought to be measured at the time the policy is implemented (the deficit shows cash flows in the current period only).

1.2.1 Relative pension loss

Pension systems provide retirees with benefits throughout their retirements, which requires looking towards the value of expected lifetime benefits. With a lifetime benefit perspective, it is easier to view many of the tradeoffs comprehensively, notably across generations. That perspective allows distinguishing between cohorts. For instance, indexation rules affect more the pension benefits of old retirees as those of newly retirees are closely tied to most recent wages.

We will compare the pension losses of all the cohorts alive in 2020 for each of our pension reforms. Given that successive cohorts have different remaining life expectancy, we use the relative pension loss by expressing the expected lifetime pension benefit under the reform relative to the expected lifetime pension benefit without reform using the survival probabilities for the different cohorts at different ages. For simplicity, we assume no discounting in the calculation.[10] Let us index each cohort s by its birth date, so that cohort $s = t$ is the cohort born in year t. So, cohort s reaches retirement age 65 in year $t = s + 65$. Retirement age is fixed throughout the analysis at 65 years, and we further assume that nobody survives beyond 100 years. We define π_t^s as the probability of a member of cohort s to be alive in year $t \geq s + 65$. The expected lifetime pension loss for cohort s under accrual adjustment reform (a_1, r_0) is:

$$\Delta^s(a_1, r_0) = \frac{\sum_{t=s+65}^{100} \pi_t^s P_t^s(a_1, r_0)}{\sum_{t=s+65}^{100} \pi_t^s P_t^s(a_0, r_0)} \tag{1.11}$$

The expected lifetime pension loss for cohort s under indexation adjustment (a_0, r_1) is:

$$\Delta^s(a_0, r_1) = \frac{\sum_{t=s+65}^{100} \pi_t^s P_t^s(a_0, r_1)}{\sum_{t=s+65}^{100} \pi_t^s P_t^s(a_0, r_0)} \tag{1.12}$$

The expected lifetime pension loss indicator is non-welfarist (it is different from lifetime utility loss). We consider this is a necessary preliminary step for a future analysis of the welfare consequences of pension reform. To measure intergenerational inequality, we will use the Gini index computed over the pension loss of each cohort. Note that this index can be related to welfare measures under certain conditions. Consider a society of n members (n large) and individual aversion for inequality, as in Fehr and Schmidt (1999). As Schmidt and Wichardt (2019) showed, simple aggregation leads to a social welfare function that can be approximated as a combination of aggregate income in society, μ, and a measure of inequality

[10] Note that discounting would introduce a cohort-specific effect due to different lifetimes when the benefit cut phases in.

in society, namely the Gini index G.[11] If this index arises naturally under certain conditions as a welfare measure, it implies a very specific form of the social welfare function. The Gini social welfare function is linear in incomes with a clear structure of increasing welfare weights for lower income individuals (see e.g. Hindriks and Myles, 2013; Cowell, 2016). It is worth noting that our (relative) pension loss equality can be related, under certain conditions, to the equal sacrifice criterion.[12] When lifetime utility is the time-separable sum of instantaneous utilities and the instantaneous utility is the Bernoulli utility function as Mill suggested, then a fixed percentage decrease in income represents the same utility loss for all (see Young, 1990, for an application of equal sacrifice to progressive taxation).

1.2.2 Voting

We assume that agents are identical inside each cohort. The agents vote over the reform that minimizes their relative pension loss. This assumption rules out altruistic behaviour across cohorts, as in Becker and Barro (1988) (we consider this possibility in Section 1.7.3). Therefore, cohort s vote for the accrual adjustment if and only if:

$$\Delta^s(a_1, r_0) < \Delta^s(a_0, r_1) \tag{1.13}$$

and for the indexation adjustment if and only if:

$$\Delta^s(a_1, r_0) > \Delta^s(a_0, r_1) \tag{1.14}$$

1.3 Example

Let us start our analysis by taking a simple example. Table 1.1 shows the demographic structure of some hypothetical ageing population. Individuals work for two periods and, then, with probability 0.5, retire during two periods. We assume a fixed contribution rate of 30%. Then, the government will match the increasing dependency ratio by either adjusting the accrual or the indexation rate, to balance the average pension budget over periods 1-3. The pension reform consists of reducing uniformly and permanently the accrual rate or the indexation rate (i.e. over periods 1-3). The dependency ratio is 55.56% at time 0. We assume

[11] Indeed, the Gini index is independent of the total level of income whereas social welfare increases if total income rises. A similar result was established earlier in Sen (1974) and Porath and Gilboa (1994) without individual aversion to inequality.

[12] The equal sacrifice doctrine can be traced back to John Stuart Mill (1884, p. 804): "As a government ought to make no distinction of persons or classes in the strength of their claims on it, whatever sacrifices it requires from them should be made to bear as nearly as possible with the same pressure upon all...that means equality of sacrifice".

a wage growth of 2% per period. The initial replacement rate is 54% at time 0 ($a_0 = 0.54$) given the initial (full) indexation rate $r_0 = 1$. The initial replacement rate equates the pension payments to the contributions in period 0 assuming a contribution rate τ_0 of 0.3. We then consider pension reforms balancing the budget constraint on average over periods 1 to 3 (i.e. the sum of the contributions over these periods is equal to the sum of the pension payments over the same time).

We compare two alternative reforms: the cohort-specific reform, changing the accrual rate, and the time-specific reform, changing the indexation rate. Let us go on with the accrual reform. At period 0 (and before), the accrual rate a_0 is 0.54 and the indexation rate r_0 is 1. Fixing the indexation rate r_0 at 1 and the contribution rate τ_0 at 0.3, the new accrual rate a_1 should be set at 32.01% for the periods 1 to 3 to balance the budget on average, even if for each period pension liabilities do not exactly match contributions. To obtain the new equilibrium accrual rate, we proceed by iteration, reducing the latter progressively from $a_0 = 0.54$ until the sum of pension payments over periods 1 to 3 equates to the sum of the contributions. The resulting equilibrium accrual rate a_1 is 32.01%. This means that the young retirees in period 2 will have, given full indexation ($r_0 = 1$), a replacement rate of 43.01% ($(54\% + 32.01\%)/2$). In period 3, the young retirees will have their entire career under the new accrual rate, and so will have a replacement rate of 32.01%. The transition from the old accrual rate (54%) to the new accrual rate (32.01%) is gradual.

Let us consider the indexation reform. We assume identical indexation before and after retirement. Fixing the accrual rate a_0 at 0.54 and the contribution rate τ_0 at 0.3, the indexation rate should be set permanently at 82.64% to balance the pension budget over the periods 1-3 (we use the same iteration method as for the calculation of the equilibrium accrual rate). In period 1, all the (young and old) retirees have the same replacement rate of 44.63% ($54\% \times 82.64\%$). The young retirees' replacement rate is reduced by the 82.64% pre-retirement indexation and the old retirees' replacement rate is reduced by the 82.64% post-retirement indexation. In period 2, the old retirees have a replacement rate of 36.88% (i.e. $44.63\% \times 82.64\%$) and the new retirees a replacement rate of 40.75% (i.e. $(54\% \times 82.64\%^2 + 54\% \times 82.64\%)/2$). A key feature of indexation adjustment is that the pension loss is greater for old retirees because the young retirees' pension benefit is tied to recent wage (time-specific adjustment). It is the opposite to accrual reform that better protects old retirees (cohort-specific adjustment).

1.4 Data

We use current cross-sectional profiles to estimate the lifetime employment profiles of the current population by considering shifts in employment rates by age. Those shifts are driven by the assumption of a continuous expansion in female labour market participation, as well as in older worker labour market participation. So, unlike the generational accounting, we do not assume that employment profiles by age are fixed over time. Our analysis uses two data sets based on such lifetime profiles. The first one is the projection of the Belgian population and employment rates by cohort, age and gender for the period 2020-2070. Those projections are done by the Federal Plan Bureau. We have the population and the employment rates projections by year and by "5 year age" bins. We expand the projection to 2100. We do so in order to cover the entire life cycle of those starting their career in 2020 (reform year). The dependency ratio in Figure 1.1 is stable beyond 2060. We expand the projection to 2100 by assuming the same demographic structure from 2070 to 2100. Indeed, the population forecast gives a steady state near 2070. For example, the fertility rate in the forecast increases from 1.54 in 2020 to 1.58 in 2027; and then remains stable at 1.71 between 2050 and 2070. The net migration, is 41 800 in 2020 and decreases to 33 900 in 2027; and then remains stable at 23 600 between 2050 and 2070 (Comité d'Etude sur le Vieillissement, 2021). We display the age structure of the population in Figure 1.2 to show the ageing challenge that Belgium will face. Given those employment and demographic projections, we compute the equilibrium accrual/indexation adjustments using (1.1)-(1.6) and (1.10).

The second data set is the survival probability of each age group as of 2019, taken from the Belgian Statistical Agency website (Statbel). Figure 1.3 shows the survival probabilities for men aged 65 and 80. This second data set is used to compute the relative pension loss induced by equilibrium accrual and indexation reforms using (1.11) and (1.12). The current cross-sectional profile of survival probability (in 2019) is assumed to retain the same shape for successive cohorts. That does not prevent life expectancy to increase since the survival probabilities by age group used for the new cohorts are higher than the survival probabilities of older cohorts. We assume that pension reform does not affect demography, but that it can change employment rates (as discussed in Section 1.7.2). The literature has shown that pension reform could affect fertility (Battistin et al., 2014) as well as mortality (Eibich, 2015; Nishimura et al., 2018). In this paper, we ignore those possible effects in order to focus on the distributional impact of the pension reform for cohorts at different ages.

1.5 Accrual versus indexation reform

We calculate the prospective consequences of accrual and indexation adjustments for each cohort (each cohort s is associated with a representative agent born in year $t = s$ with cohort-age specific wage and survival probabilities). We assume that each cohort works a full career lasting 45 years (i.e. we do not consider pension policy extending the career requirement). We assume a wage growth of 2% per year and a contribution rate τ_t of 30%. We will relax this fixed contribution assumption later to consider simultaneous adjustment of pensions and contributions. The pre-reform dependency ratio is 43.06% in 2019; and the pre-reform benefit ratio is set at 69.68%, so that the pension budget is balanced in 2019. The dependency ratio is expected to rise on average from 43.06% to 54.93% over the period 2020-2100, inducing for fixed contributions an average decrease in the benefit ratio from 69.68% to 54.61%. Our analysis starts by studying the distributional effects of balancing the budget exclusively with accrual or indexation adjustment to match the predicted increase of the dependency ratio over the period 2020-2100.

1.5.1 Accrual reform

In case of an accrual adjustment, the new equilibrium accrual rate a_1 is 45.99% (fixing the indexation rate r_0 at 100% of the wage growth) to balance the budget over the period 2020-2100. The initial accrual rate a_0 is 69.67%. Figure 1.4 shows the evolution of the replacement rate over time for (successive) cohorts reaching either 65, 80 or 95 years old in year t in case of an accrual adjustment. As illustrated in our example, the replacement rate reduces gradually over time. It decreases until 2065 for successive cohorts reaching 65 years. In 2065, the system is totally phased in given the career length of 45 years. The replacement rate stays constant from this point on, because the following cohorts will also have their entire careers with the reduced accrual rate (45.99%). There is a parallel evolution of the replacement rate for the successive cohorts reaching 80 and 95 years old in time t. The comparison of replacement rates across different age cohorts is as follows. Consider year 2065. The 65 years cohort will have a full career (45 years) with the new accrual rate producing a replacement rate of 45.99%. The 80 years cohort will have $1/3$ of its career with the old accrual rate a_0 of 69.67% and the rest with the new one a_1 of 45.99%. The 95 years cohort will have $2/3$ of its career with the old accrual rate and the rest with the new one. As in our simple example, the adjustment through the accrual rate induces heterogeneous replacement rates for different cohorts of retirees during the transition. The older cohorts are the least impacted by this cohort-specific accrual adjustment.

1.5.2 Indexation reform

In case of a time-specific reform, such as the indexation adjustment, the equilibrium indexation rate is 99.05% of the wage growth (fixing the accrual rate a_0 at its initial level of 69.67%) to balance the budget over the period 2020-2100. Under this type of adjustment, the replacement rate also decreases gradually over time. However, unlike the accrual adjustment, all cohorts are impacted by the indexation adjustment. As explained in our simple example, indexation spreads the adjustment costs across all cohorts. In our simulation, the gap between the replacement rate at 65 years of the newly retired in 2020 and the future retirees in 2100 is 13.19 compared to a gap of 23.69 under the accrual rate adjustment. So, the "pension" gap is halved when adjusting the pensions via the indexation rather than the accrual rate. The replacement rate across cohorts and over time is illustrated in Figure 1.5. Under the indexation adjustment, the replacement rate of the newly retired at any time t is always higher than the replacement rate of the older retirees. The indexation adjustment reduces the pension inequality between cohorts already retired and newly retired cohorts at the cost of increasing the pension inequality among already retired (young and old) cohorts.

1.5.3 Comparing pension loss

Figure 1.6 compares the relative pension loss of each cohort alive in 2020 under either the accrual reform or the indexation reform. Note that without reform, there is full indexation both before and after retirement and all cohorts face the same accrual rate over their entire careers. Therefore, our baseline of no reform involves the same lifetime pension benefit across cohorts. The reform will impact differently the different cohorts producing a gap in lifetime pension benefits. When comparing the two reforms, Figure 1.6 indicates that the pension loss is larger under accrual reform for cohorts below 30 years (in 2020) and larger under the indexation reform for cohorts above 30 years (in 2020). It means that if there was a vote in 2020 on either of these two reforms, those younger than 30 years would support the indexation reform and those older than 30 years would support the accrual reform. Recall that we assume that people vote in favour of the reform minimizing their pension loss. Since the median voter in 2020 in Belgium is 50 years old, a majority would support the accrual reform (in fact, a majority of 80% would support the accrual reform).

1.5.4 The democracy-equality generational tradeoff

The voting outcome over pension reforms looks inequitable if we want to achieve some generational balance in the sharing of the ageing cost (i.e. pension loss). The accrual reform is more unequal than the indexation one. The Gini index of the pension loss is 43.07% for the accrual adjustment, whereas it is 21.56% for the indexation reform. To further illustrate the generational inequality, we employ the Lorenz curve. We adapt the Lorenz curve in our generational framework to represent the proportion of the total pension loss (relative to the no reform baseline) born by the youngest $x\,\%$ of the population alive in 2020. As we see in Figure 1.7, 85% of the total pension loss is born by the youngest half of the population under the accrual reform, whereas it is 65% under the indexation one. The size of the generational inequality in sharing the burden of adjustment is striking because we impose an immediate and permanent adjustment (no procrastination cost) and also because we restrict the inequality to the generations alive at the time of the reform.[13] The democracy-equality tradeoff is driven by the gradual phase in of the reforms with the grandfather clause ruling out retrospective adjustments. The nature of the problem is not new. The problem of democracy is that representation is not proportional to the stakes (Brighouse and Fleurbaey, 2010). First, cohorts aged less than 18 and the future generations are not allowed to vote even though they are affected by current reforms. To reverse the voting outcome in favour of indexation reform, we should give a vote to people under 18 and to all cohorts not yet born in 2020 at least until future cohorts born in 2036. An alternative solution would be to use constitutional rules to protect future cohorts. Second, there are people who have a vote, but their vote is not proportional to the stake in the current decision. This is a general concern with elections that takes a very acute form with pension reform. In the following section, we will consider alternative pension policies that can improve the generational equality but will still face the fundamental democracy-equality generational tradeoff.

1.6 Other pension policies

So far, we have analysed the distributional effects of using either the accrual or the indexation rate adjustment in response to the rising dependency ratio. We have seen that both adjustments have their own drawbacks. The accrual adjustment increases the pension gap between current and future retirees. Indexation adjustment increases the pension gap between young and old retirees. In this section, we consider alternative adjustments to attenuate those pension inequalities. First, we consider a policy mix (i.e. combining accrual and indexation adjustments). Then, we analyse the dual indexation that allows to use different indexation rates before and after retirement. Third, we consider simultaneous adjustment of pension benefit and contribution rate tied down by the "Musgrave (1981) rule" requiring

[13] Inequality would further increase if we considered the pension loss for the future generations not yet born in 2020.

equiproportional change in contribution and benefit rates.

1.6.1 Policy mix

It is possible to combine accrual and indexation changes in order to reduce the generational pension inequality. We know that cohorts already retired at the time of the reform do not contribute to the overall effort under accrual adjustment and that the pension loss is more equally distributed across cohorts with indexation adjustment. So in order to reduce the pension loss inequality, the policy mix option is to increase the accrual rate above its pre-reform level, and to compensate by decreasing further the indexation rate. In doing so, cohorts already retired will face greater erosion of their pensions during retirement. And the newly retired cohorts will benefit from the higher accrual rate. As a result, the generational pension loss inequality will decrease. Table 1.2 shows the Gini index for different policy mixes. The first two rows of the table indicate the benchmark cases, respectively accrual change only and indexation change only. The last three rows indicate various policy mixes with increasing accrual rate and decreasing indexation rate. The Gini inequality decreases as we shift more of the adjustment from the accrual to the indexation. Although those combinations decrease the inequality, they do not get more political support than a pure indexation reform. Figure 1.8 shows the pension loss by age with the mix adjustment minimizing generational inequality. We see that the pivotal age for this mix adjustment against accrual adjustment merely increases from 30 to 32. We still have a vast majority in favour of accrual adjustment. The generational democracy-equality tradeoff is persistent.

1.6.2 Dual indexation

Another solution to decrease generational inequality is to differentiate the pre-retirement and post-retirement indexation rates (dual indexation). We analyse this possibility in Table 1.3 given a fixed accrual rate a_0 of 69.67%. The first column indicates the ratio of the post-retirement to the pre-retirement indexation. To minimize pension loss inequality, the post-retirement indexation should be less than pre-retirement indexation (since the older cohorts are less impacted by the gradual reforms). We see that the Gini index decreases as the pre- to post-retirement indexation gap increases.

We compare the pension loss inequality under accrual reform and dual/uniform indexation reforms in Figure 1.9. The figure assumes a dual indexation with a pre-retirement indexation of 1 and a post-retirement indexation of 0.96. The break even age is 36 years with those younger preferring the dual indexation and those older preferring the accrual reform. Switching to dual indexation shifts the burden from the younger cohorts to the cohort reaching retirement age at the time of the reform. Given the current median voter age, there is almost a fifty-fifty divide between the two indexation options. A large majority still prefers accrual adjustment to any form of indexation adjustment, confirming the generational democracy and equality tradeoff.

1.6.3 Musgrave rule

So far, we have fixed the contribution rate at 30%. We now relax this assumption by considering a joint adjustment of pension benefits and contribution rate. The set of possible combinations of pension benefit and contribution adjustments is infinite, so we will tie down the reforms using the Musgrave rule. The Musgrave (1981) rule requires keeping constant the ratio of the pension benefit to the net wage. This means that to maintain budget balance when the dependency ratio increases, both the pension benefit β_t and the contribution rate τ_t should be adjusted in equal proportion to maintain the ratio $\frac{\beta_t}{1-\tau_t}$ constant. As we have different pension benefits, we apply this rule by considering that the ratio of the pension benefit of someone aged 65 compared to the net wage should be the same before and after the reform is fully phased in.

Following Musgrave rule, under accrual adjustment, the contribution rate increases from 30% to 37% and the accrual rate decreases from 69.68% to 62.71%. Under indexation adjustment, the contribution rate is 35.66% and the indexation rate is 99.62%. To compare the distributional effect of this "Musgrave" adjustment with the fixed contribution scenario, we need to add the contribution adjustment to the pension loss for those working at the time of the reform. Interestingly, as shown in Figure 1.10, the pivotal age (around 30 years) does not change with the Musgrave adjustment. The reason is that mixing contribution increases with benefit cuts does not really change the relative preference over accrual and indexation adjustments. What it does is to scale down the size of the accrual/indexation adjustment, and so the size of the pension loss for those currently working. However, this is offset by the increase in their contributions. So, the Musgrave reform operates a lifetime shift for the working cohort between pension and contribution without changing the conflict of preferences across cohorts.

1.7 Extensions

1.7.1 Unequal longevity

We have assumed representative agents within each cohort. Introducing heterogeneity within cohorts is necessary but complex. Indeed, forecasting the lifetime income and employment rates profiles of future cohorts of low- and high-skilled workers based on the cross-sectional observations of the lifetime profiles of the current population is problematic (Banks et al., 1999). Unequal longevity is very relevant in our prospective analysis because when life is short cohort-specific or time-specific gradual adjustments do not have the same effect as when life is long. We will provide a first-order approximation to the case of unequal longevity within cohorts. Chetty et al. (2016) find that in the US, the gap in life expectancy between the richest 1% and poorest 1% of individuals was 14.6 years (95% CI, 14.4 to 14.8 years) for men and 10.1 years (95% CI, 9.9 to 10.3 years) for women. Eggerickx et al. (2020) find that in Belgium, the probability to reach 65 years (retirement age) is 77% for the low-income group and 93% for the high-income group. We introduce within cohort unequal longevity in our simulation model by indexing mortality rates from Statbel by the income-specific coefficients in Eggerickx et al. (2020). Those longevity coefficients are the delta between the average mortality rates in the population and the mortality rates specific to the low/high-income groups.

Figure 1.11 compares the male survival probabilities in the low/high-income groups. We can see that the low-income group faces a probability of 23% of not reaching retirement age against a probability of 7% in the high-income group. The other gap is the difference in the pension duration. Life expectancy for low socioeconomic status is 57.93 at 18 and 17.08 at 65 and is 65.83 at 18 and 20.87 for high socioeconomic status. Someone with a shorter life expectancy will prefer a higher benefit at the beginning of retirement, and so she may prefer indexation adjustment to accrual adjustment. Let us compare the pension loss for both income groups. Note that the pension benefit is proportional to income and so only longevity gaps will influence the relative pension loss between income groups. First, the pension loss (relative to no reform) with the accrual rate is the same for both income groups. Indeed, the pension loss depends on the sum of the probabilities of being alive at a particular age (π_t^s) times the retirement benefit (P_t^s) at that age ($\sum \pi_t^s P_t^s$). With an accrual adjustment (and full indexation), the pension benefit profile does not change during retirement. As a result, the longevity gap has no incidence on the pension loss under accrual adjustment for either income group. However, indexation adjustment erodes pension benefits during retirement and thus the long-lived (high-income group) are more affected by this adjustment. Inversely, the short-lived (low-income group) may prefer to trade off lower indexation for higher accrual. This conjecture is confirmed in our simulation results (using Eggerickx et al. (2020)'s income gap in mortality rates), with the pivotal age between accrual and indexation reforms being shifted up to 32 years (against 31 years for the high-income group, see Figure 1.12). What is striking is that the distribution of preference over accrual and indexation adjustments does not change much, even though the longevity gap in our simulation is quite high. This suggests that our tension between democracy and equality is quite robust to (growing) longevity inequality.

1.7.2 Endogenous labour force participation

Retirement incentives are essential for pension reforms. In order to capture retirement incentives in a simple way, we assume that the reform will change the employment rates of different cohorts, proportionally to their pension loss and the employment elasticity. Given those assumptions, we calculate the expected reduction of pension benefits needed to balance the intertemporal budget in the presence of employment response and compare the accrual and the indexation reforms. We consider the aggregate elasticity averaging behavioural responses across individuals with heterogeneous preferences over income and leisure (some workers are willing to trade off lower pension for longer pension and other workers are not). We will further assume that the change in the employment rates is restricted to the end of the career (young workers do not really adjust their labour supply to the change in their future pension benefits). We consider that the employment rates of the 60+ are related to the pension benefit loss according to the following sufficient statistic:

$$\frac{e^0 - e^s}{e^0} = Elasticity \times Pension\, loss^s \tag{1.15}$$

where e^0 is the baseline employment rate. The percentage change in the participation rates of cohort s (60-65 years) is proportional to their pension loss (in %). Since the pension loss differs across cohorts, the change in participation rates will also differ across cohorts. One particular important parameter is the value of the elasticity with regard to the pension loss.

Blondal and Scarpetta (1998), Gruber and Wise (2001) and Blanchet et al. (2019) argue that individuals are often induced to retire early because of the large implicit tax imposed on continuing to work after early retirement age, which has a direct impact on the employment rate of elderly workers. Our central driver for retirement incentives is the link between contribution and pension benefit (Andersen et al., 2019; French et al., 2022). So, when reducing the accrual rate in our reform, we also weaken the link between contribution and pension benefits, which reduces the return to work. Pension reform in Poland, involving a sharp cohort-specific discontinuity in the link between current contributions and future benefits, led to employment elasticity with respect to the return to work (including future pension benefits) of 0.44 (French et al., 2022). In this perspective, the employment elasticity is positive in equation (1.15). The pension loss reduces the employment of elderly workers and tightens up the (intertemporal) budget constraint. Table 1.4 shows the change in the accrual and the indexation rates as a function of the employment elasticity using (1.1)-(1.15).

An alternative perspective is that generous pension benefits reduce incentives to work longer (Giesecke and Jäger, 2021). Gruber and Wise (2001) suggest that generous early retirement provisions are largely responsible for the drop in the participation rates. The argument is that individuals do not need to continue work and are able to live with their (generous) pension benefits and, as a result, quit the labour force (Börsch-Supan, 2000; Gruber and Wise, 2001; Danzer, 2013). Following this perspective, the pension loss would provide incentives to work longer, relaxing the intertemporal budget constraint. It is represented in the bottom part of Table 1.4 with negative employment elasticity.

A central feature of the simulations with the positive elasticity is that the benefit cut lowers employment rate among elderly workers. However, the benefit cut via the indexation reform creates fewer changes in employment rates than the benefit cut via the accrual rate. In that sense, the indexation is preferable to the accrual reform in terms of employment change. The result of the vote does not change when we add endogenous employment.

1.7.3 Altruistic voting

In this section, we consider the case of altruistic voters. The different cohorts are still composed of representative agents; but those agents have a child born when they were 30 years old.[14] So, they do not only care about the outcome of the votes for themselves, but also for their children. As a result, (1.13) becomes:

$$\Delta^s(a_1, r_0) + \phi\Delta^{s+30}(a_1, r_0) < \Delta^s(a_0, r_1) + \phi\Delta^{s+30}(a_0, r_1) \tag{1.16}$$

[14] In Belgium, women have - on average - their first children at 31 years old (Statbel, 2022).

where $0 \leq \phi$ is the intergenerational discount rate. (1.14) becomes:

$$\Delta^s(a_1, r_0) + \phi\Delta^{s+30}(a_1, r_0) > \Delta^s(a_0, r_1) + \phi\Delta^{s+30}(a_0, r_1) \tag{1.17}$$

We only consider the case where the agents care about their children, but not about their grand-children and all future generations. As a result, three different cases exist:

- People aged above 60 do not change their votes. The accrual adjustment is the best option for them as well as for their children.
- People aged between 30 and 60 can change their votes depending on the value of ϕ.
- People aged less than 30 do not change their votes. The indexation adjustment is the best option for them as well as for their children.[15]

The vote of those aged between 30 and 60 will decide the outcome of the vote. Recall that the median voter in Belgium is aged 50 in 2020. The value of ϕ will be the crucial parameter to switch from an accrual to an indexation reform. We have plotted the pivotal age as a function of ϕ in Figure 1.13. An accrual reform will be preferred unless ϕ takes, at least, a value of 1.18. This means that voters should care more about their children than themselves.

1.8 Conclusion

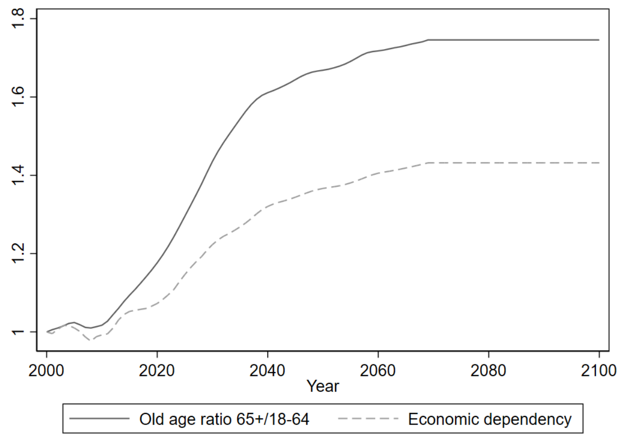
In this chapter, we provide a first order approximation of the prospective consequences for all generations currently alive of different pension policies seeking to secure the long term budget balance of the pay-as-you-go pension schemes in an ageing population. We stick to an actuarial evaluation of the effects by considering the relative pension loss. The relative pension loss is the change in the lifetime pension benefit relative to the no reform status quo. The central finding of our simulation model is the tension between equality and democracy. Equality across cohorts requires in our model to adopt pension reforms minimizing the gap in the relative pension loss across cohorts currently alive. Our approach is in the spirit of generational accounting since we calculate how much in total each current and future retiree can expect to pay in terms of pension loss over their remaining expected lifetimes. We focus on incidence across cohorts, and so we assume representative agents within cohorts. We use a cross-sectional prediction of future life-cycle income and employment profiles with updating

[15] Individuals have their children when they are 30 years old. We assume that younger generations will also have a child in the future.

for wage growth. We impose a term limit to the intertemporal budget balance to avoid the Ponzi perpetual roll over of the budget deficit to future generations.

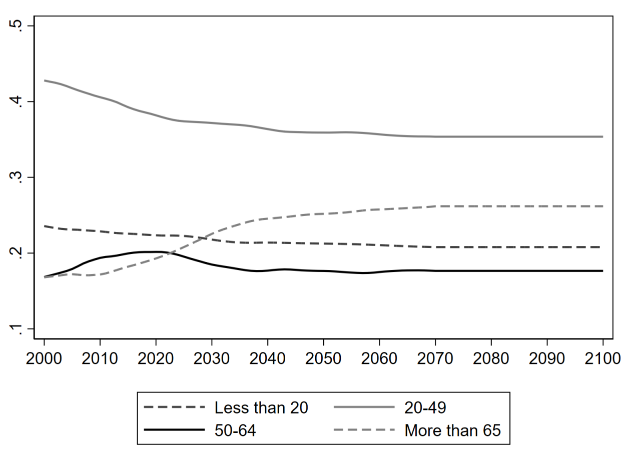
We find that indexation is preferable to accrual reform in terms of generational balance, but that around 80% of the voters would oppose to the indexation reform. We find that as a result of the voting outcome, the youngest half of the cohorts currently alive will bear 85% of the total adjustment cost. We also show that it is possible to improve further the generational balance by combining accrual and indexation reforms. In particular, generational balance would require a higher accrual rate combined with a lower indexation rate to shift further the adjustment cost to the cohorts already retired. An alternative policy option would be to set the before-retirement indexation to be higher than the after-retirement one. However, these two policy options would be opposed by a majority of voters currently alive. We show that the tension between democracy and equality is robust to the introduction of unequal longevity within cohorts and, in some cases, to the inclusion of altruistic voting.

Our results are a first-order approximation of the prospective incidence of pension policies on all cohorts currently alive. One interesting follow-up would be to go further than an actuarial dimension and consider welfare analysis. In particular, Fleurbaey et al. (2016) have shown that utilitarianism treats badly people with a short lifespan. However, in this chapter, the individuals with a short lifespan are those already in retirement. A detailed analysis of the pros and cons of using utilitarianism in the context of our chapter could lead to the fact that utilitarianism is good to protect the young generations. A welfare analysis could also incorporate the lifetime income of the different cohorts - an important point that is not taken into account in our Gini indicator of relative pension loss. Another interesting follow-up would be to go for a more structural analysis of the impact of pension policies taking into account within cohort heterogeneity of lifetime income, employment and mortality profiles together with endogenous behavioural responses, using microsimulations. A central assumption that we made is that representative agents in each cohort are assumed to follow the same age profiles of mortality, earnings, employment and retirement which are the currently observed age profiles in the cross-section data with updating for growth. This cross-sectional prediction of life-cycle profiles is problematic when there is heterogeneity within cohorts. We have already shown that individuals near retirement with a short life expectancy could prefer the indexation adjustment to the accrual one. Considering inside cohort heterogeneity could lead to other interesting results. Finally, a follow-up would be to analyse the possibility to correct democracy to better consider the fate of the young generations. Those are interesting avenues for future research.



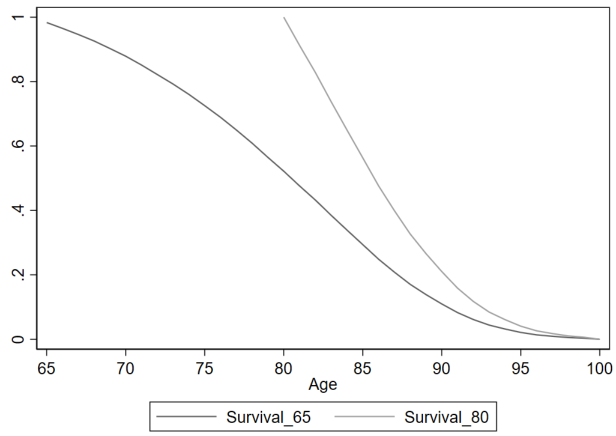
The figure shows the economic and demographic dependency ratio of Belgium. The data used comes from the Federal Plan Bureau for the period 2000-2070 and we expand them until 2100.

Figure 1.1: Economic dependency and old-age ratio (base year 2000=100)



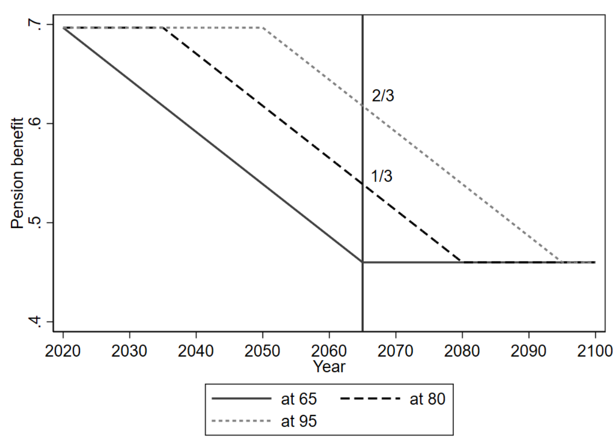
The figure shows the structure of the population in Belgium between 2000 and 2100. The data used comes from the Federal Plan Bureau for the period 2020-2070 and we expand them until 2100.

Figure 1.2: Population structure



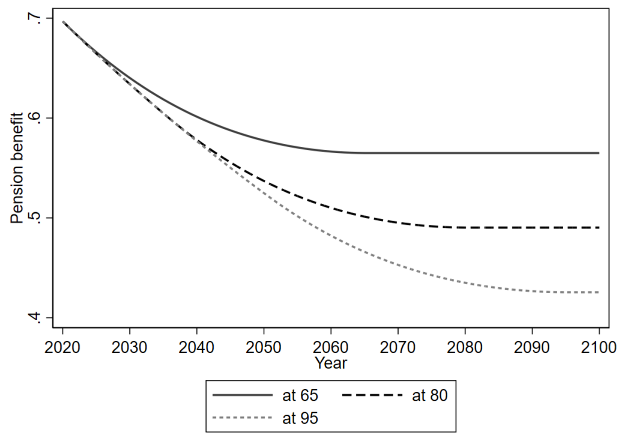
The figure shows the survival probabilities of men aged 65 and 80 in 2020. The data comes from Statbel (Belgian Statistical Office).

Figure 1.3: Survival probabilities of men at 65 and 80.



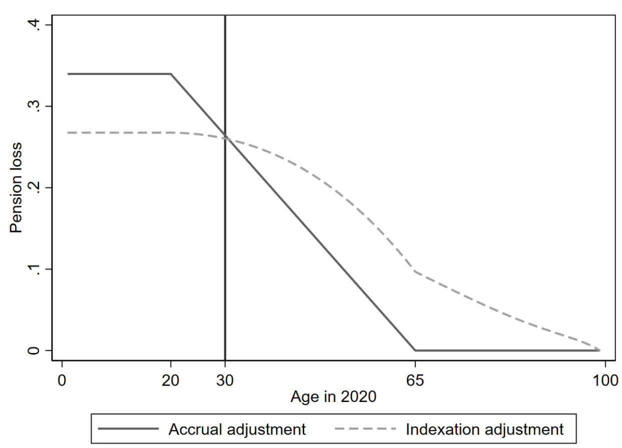
The figure shows the replacement rates for individuals aged 65, 80 and 95 in case of an accrual reform. The replacement rates decrease as the reform is phased-in. In 2065, the reform is totally phased-in for those aged 65 while the older still have a part of their career with the previous accrual rate.

Figure 1.4: Replacement rates at 65, 80 and 95 by year with accrual reform



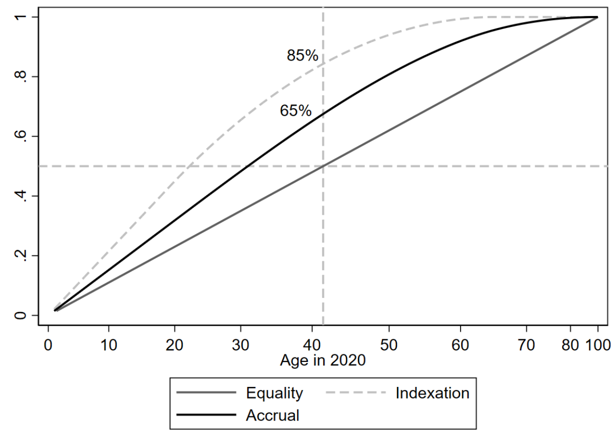
The figure shows the replacement rates for individuals aged 65, 80 and 95 in case of an indexation reform. The replacement rates decrease as the reform is phased-in. Contrary to the accrual reform, the replacement rates decrease from the start of the reform.

Figure 1.5: Replacement rates at 65, 80 and 95 by year with indexation reform



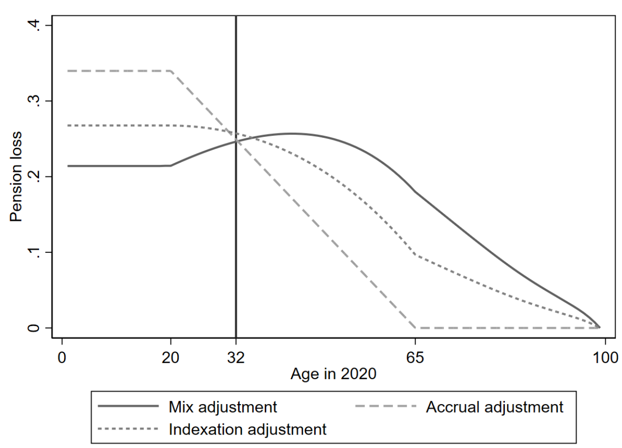
The figure shows the pension loss by age (at the time of the reform). The pension loss is the relative loss between the expected pension wealth with a reform compared to the pension wealth without reform. The individuals older than 30 prefer an accrual reform while the youngest prefer an indexation reform.

Figure 1.6: Pension loss (relative to no reform) as a function of cohort age in 2020



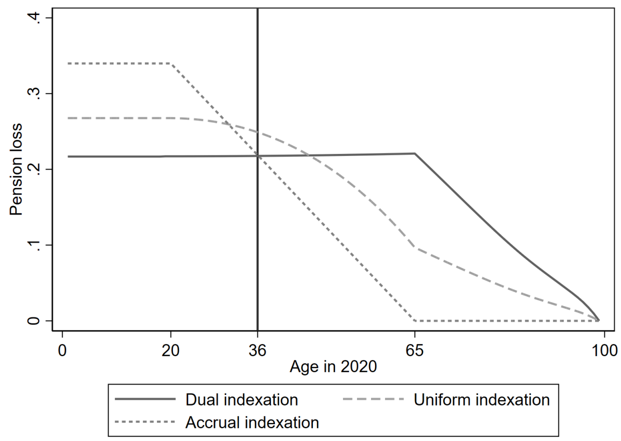
The figure shows the Lorenz curve of the distribution of the cost of the pension reform. The youngest half of the population bears more the costs than the older ones. The indexation reform spreads more the costs than the accrual one.

Figure 1.7: Proportion of total costs born by the youngest $x\%$ of the population as a function of cohort age in 2020



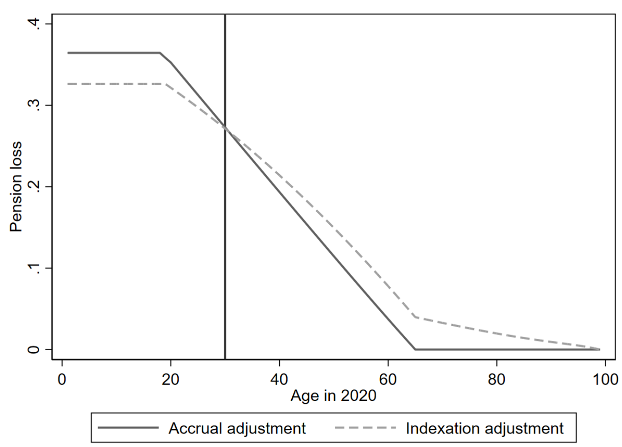
The figure shows the pension loss for the accrual, indexation and the best (i.e. the one with the lowest Gini index) mix adjustments. The best mix adjustment is an accrual rate of 100.00 % and an indexation rate of 98.12 %.

Figure 1.8: Pension loss for the accrual, indexation and (best) mix adjustment



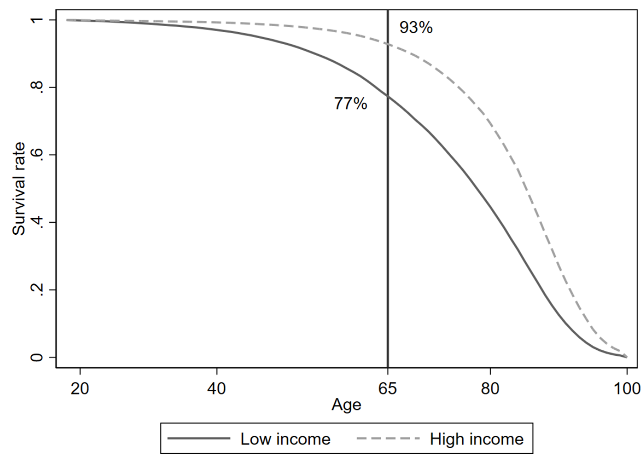
The figure shows the pension loss for the dual indexation and the uniform indexation. The dual indexation means that the indexation rate is different before/after retirement.

Figure 1.9: Pension loss (relative to no reform) - Accrual, uniform and dual indexation reforms



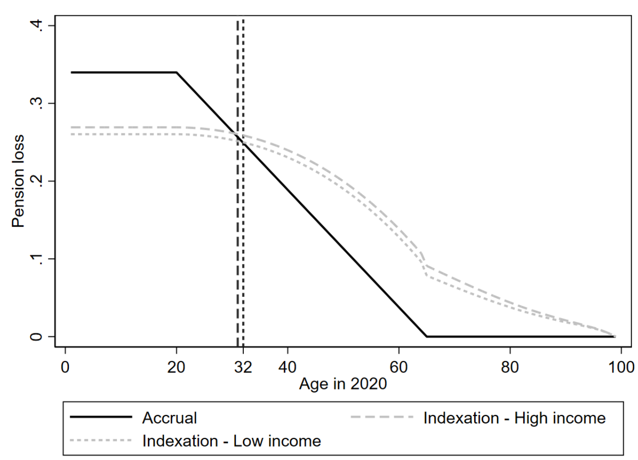
The figure shows the pension loss with a Musgrave reform. The Musgrave reform is done by decreasing the pension benefit and increasing the contribution rate such that the ratio pension benefit/net wage stays constant.

Figure 1.10: Pension-net wage loss (relative to no reform) under Musgrave rule



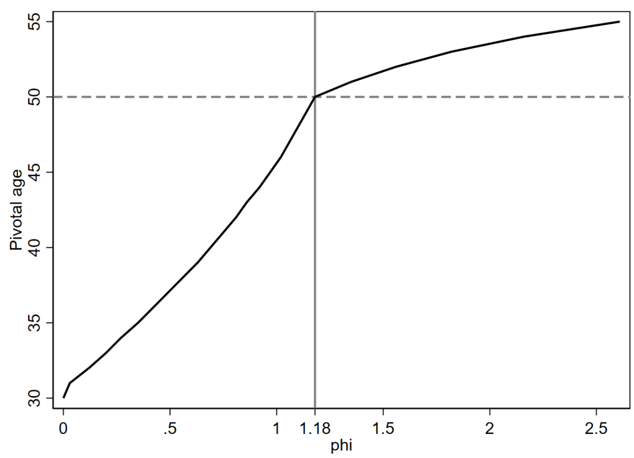
The figure shows the survival rate for the low/high-income group in Belgium. The average mortality rates come from Statbel (Belgian statistical agency) and the mortality rate deltas come from Eggerickx et al. (2020).

Figure 1.11: Survival probabilities for male with low- and high-income



The figure shows the pension loss for the accrual and the indexation adjustments for the low- and high-income group (male). The pivotal age is higher for the low-income group.

Figure 1.12: Pension-net wage loss by income group (male) - Musgrave



The figure shows the pivotal age as a function of ϕ. The pivotal age increases as the level of intergenerational altruism increases. At 1.18, the median voter votes for the indexation adjustment.

Figure 1.13: Pivotal age as a function of ϕ

Period	Demographic structure				Dependency ratio	Accrual adjustment		Indexation adjustment	
	Young Workers	Old Workers	Young Retirees	Old Retirees		Young Retirees	Old Retirees	Young Retirees	Old Retirees
0	8	10	5	5	55.56%	54.00%	54.00%	54.00%	54.00%
1	6	8	5	5	71.43%	43.01%	54.00%	44.63%	44.63%
2	6	6	4	5	75.00%	32.01%	43.01%	40.75%	36.88%
3	3	6	3	4	77.78%	32.01%	32.01%	40.75%	33.68%

The table illustrates the pension system with accrual and indexation adjustments. The system is in balanced at time 0 and a reform is done for the period 1-3. The accrual adjustment takes time to be phased in, which requires a lower pension benefit for the youngest cohorts.

Table 1.1: Simple Illustration

	Accrual rate	Indexation rate	Gini index of the pension loss
Accrual adjustment	45.99%	100,00%	43.07%
Indexation adjustment	69.67%	99.05%	21.56%
	80.00%	98.71%	16.26%
	90.00%	98.40%	13.32%
	100.00%	98.12%	11.90%

The table shows the pension loss and the Gini index of the pension loss for different policy mix. The two first lines are the extreme cases (accrual only or indexation only). The Gini index decreases as the accrual rate increases and the indexation rate decreases.

Table 1.2: Policy mix reforms and generational pension loss inequality

Ratio	Post-retirement indexation	Pre-retirement indexation	Maximum Pension Loss	Gini index
	100.00	98.35	30.05	33.81
1.01	99.62	98.63	28.83	28.75
1.00	99.05	99.05	26.77	21.56
0.99	98.47	99.46	24.63	14.67
0.98	97.86	99.86	22.44	8.04
0.976	97.61	100.01	22.08	5.94
0.97	97.23	100.24	24.92	7.07

The table shows the Gini index, the maximum pension loss and the indexation rates in case of dual indexation. The dual indexation means that the indexation rate is different after/before retirement.

Table 1.3: Dual indexation and generational pension loss inequality

Elasticity	Accrual rate	Employment rate (Age: 60 in 2065) Accrual adjustment		Indexation rate	Employment rate (Age: 60 in 2065) Indexation adjustment	
		Male	Female		Male	Female
0.5	44.06	56.30%	46.42%	98.97	59.10%	48.72%
0.4	44.47	59.00%	48.64%	98.99	61.20%	50.45%
0.3	44.87	61.63%	50.81%	99.01	63.23%	52.13%
0.2	45.25	64.13%	52.87%	99.02	65.17%	53.73%
0.1	45.63	66.58%	54.89%	99.04	67.12%	55.33%
0	45.99	68.96%	56.85%	99.05	68.96%	56.85%
-0.1	46.35	71.30%	58.78%	99.07	70.80%	58.37%
-0.2	46.72	73.65%	60.71%	99.08	72.65%	59.89%
-0.3	47.08	75.99%	62.65%	99.10	74.49%	61.41%
-0.4	47.45	78.33%	64.56%	99.11	76.34%	62.93%
-0.5	47.82	80.68%	66.51%	99.13	78.18%	64.45%

The table shows the accrual rates and the indexation rates when taking into account the impact on the employment rate of benefit cut. Positive (negative) elasticity implies that the benefit cut reduces (increases) the senior labour force participation. As a result, the accrual/indexation rates are lower (higher).

Table 1.4: Accrual and indexation reforms with work incentives near retirement

Chapter 2

Inferring occupation arduousness from poor health beyond the age of 50

Co-authors: Sandy Tubeuf & Vincent Vandenberghe

This chapter shows that the pension policy-maker with no direct information on the arduousness of different occupations could reasonably infer it from the correlation between old-age health and career history. Using retrospective lifetime data from the Survey of Health, Ageing and Retirement in Europe, including the respondents' occupational career described at ISCO 2-digit level, this chapter finds evidence that the main occupation is predictive of the health status beyond 50, even after conditioning on pre-labour-market entry controls (e.g. childhood health). The underlying ranking of occupations is stable and could be used to implement a retirement differentiation policy aimed at compensating for occupational arduousness. Next, we quantify the degree of career length differentiation that would be required to compensate for the occupational arduousness differences. Results suggest it would be quite significant, with a gradient of 15 years between the most and least arduous occupations. Finally, using variance-decomposition methods, we try to quantify the relative contribution of occupations to predict old-age individual health differences. We find that occupation arduousness - although a significant predictor of poor health - is less consequential than initial health endowment, demographics or country fixed effects; stressing the importance of policies targeting the early years of life.

2.1 Introduction

The rise of average healthy life expectancy calls for an overall increase in the age of retirement. However, many observers suggest that to preserve retirement equality, the age of retirement should be differentiated (see e.g. Vermeer et al., 2016). Same-age old individuals differ a lot in terms of health (Wise, 2017; Vandenberghe, 2021) and also as to their remaining (healthy) life expectancy.[1] There is strong evidence that ill-health at 50 is correlated with a shorter lifespan/early death. De Nardi et al. (2016) show that lifespan is 3.3 years shorter for those with bad health than for those with good health, while Pijoan-Mas and Ríos-Rull (2014) show the equivalent numbers are 5.6 for men and 4.7 for women at age 50.

Historically, in most retirement systems, a uniform age has been used as a proxy for poor health, the ensuing loss of work capacity and remaining (healthy) life expectancy. But now comes this proposition to adopt a slightly more refined proxying strategy. This consists of using several retirement ages to better match the distribution of late years health status and work capacity across socio-demographic groups, and in particular across occupations that vary a lot in terms of their arduousness. Many stakeholders, but also economists (e.g. Ayuso et al., 2017) call for the abolition of the uniform age of retirement as well as using the career length instead of a fixed retirement age (see e.g. Schokkaert et al., 2020).[2] Paradoxically, the implementation of this idea seems complicated. There is a lack of a direct and consensual measure of arduousness and its actual contribution to the risk of poor health/short life beyond 50. This is one of the reasons why governments struggle to implement it. "Arduous" jobs are often defined more or less arbitrarily. An exception is perhaps Poland, where daily calories needed to perform the job have been used to evaluate the arduousness of a profession (see e.g. Zaidi and Whitehouse, 2009). Still, some sedentary occupations might not require as many calories as manual work, but could also be detrimental to health.

This chapter aims at clarifying the above debate. It contributes to the economic literature on career length differentiation and demanding occupations (Pestieau and Racionero, 2016; Vermeer et al., 2016; Vandenberghe, 2021). More generally, it adds to the work-health literature, by exploiting unique, and so far untapped retrospective data on careers, together with very detailed data on health beyond the age of 50. Finally, this chapter relates to the life course literature as it stresses the role of pre-labour market entry determinants of late-years health (Trannoy et al., 2010). The impact of work on health has long been investigated by the eponymous work-health literature in epidemiology, psychology, and sociology literature; but to a lesser extent in economics (for a review of the literature, see Bassanini and Caroli, 2015;

[1] In Belgium, for people that entered the labour market at the age of 20, there is a 10% risk that they will not reach the uniform age of retirement of 65. At this age, the remaining life expectancy gradient is in the range of 8 to 10 years considering gender×education socioeconomic categories.

[2] To take into account the issue of career start heterogeneity.

Barnay, 2016). Most research and policy debates underline various negative consequences of work and working conditions such as stress, physical exhaustion, work-related disabilities, overall poor health as well as premature death.

Borg and Kristensen (2000) show that the socioeconomic gradient in health coexists with a socioeconomic gradient in working conditions. Using data from the US National Health Interview Survey (NHIS), Case and Deaton (2005) show that manual workers, with low education or low wealth, have higher rates of health deterioration and that their physical health will deteriorate more rapidly with age than non-manual workers. However, overall, economists have been cautious at interpreting these correlations as evidence of a causal effect of occupation on health (see Ravesteijn et al., 2013, for a thorough literature review). The main problem is that individuals in poor health could not only face reduced employment opportunities, but could also self-select in specific jobs because of their health status. In order to overcome this issue, Sindelar et al. (2007) have assessed the impact of the first occupation on later health. Their underlying assumption is that health should be homogeneous at the start of the career. However, several studies have shown that health may already differ at entry in the labour market. Holland et al. (2000) show that individuals that were socially disadvantaged during their childhoods have a higher probability to end up in harsh occupations. To cope with this problem, Fletcher and Sindelar (2009) use the father's occupation or the US State economic conditions at the start of the career to instrument respondent's first occupation. But the exogeneity of both instruments could largely be questioned, as they are likely to affect health directly. Fletcher et al. (2011) combined external information on the physical requirements of work and environmental conditions with data from US Panel Study of Income Dynamics to estimate the health impact of exposure to physical and environmental conditions at work. However, they failed to establish a causal effect of occupation on health. More recently, Morefield et al. (2012) and Ravesteijn et al. (2018) have considered dynamic models controlling for health status at different time points. When controlling for lagged health one year before, Ravesteijn et al. (2018) found that at least 60% of the correlation between occupation and health is due to people with worse health self-selecting into specific occupations. In short, arduousness as the impact of occupation on health is not easy to estimate.

Beyond the link between work/occupation and health, there is another stream of the economic literature that shows that past (in particular early life) personal experience can undermine health and professional pathways cumulatively over the life course (Lindeboom, 2012). There are long-lasting effects of family and social background on health status in adulthood. Three concurrent channels of transmission from one generation to another have been identified (Trannoy et al., 2010): a direct channel where social background influences adult health following a latency period; an indirect channel where social background influences health through its impact on employment and life trajectories; and the third channel is an intergenerational transmission of health a common genetic capital within families. More generally, a large body of literature equally acknowledges the role played by the social determinants of health (Marmot and Wilkinson, 2005). Such selection effects from early life experience must also be taken into account to measure the net effect of work on health.

Our contribution to the above literature is essentially twofold.

- The first one is our demonstration that *career arduousness* - at least when it comes to *ranking* the main occupations that people have exerted - could relatively easily be inferred from health data in the European context in the absence of direct and detailed measures of arduousness. There exist surveys providing direct estimates of average arduousness by occupation. An example is the US Occupational Information Network (O*Net),[3] that provides an impressively detailed description of working conditions for almost 1,000 professions, or its less known and less detailed European counterpart, the European Working Conditions Survey (EWC).[4] However, those surveys are no panacea for two reasons. First, they require governments to collect a lot of (new) data. Second, they are not able to summarize the career arduousness in one indicator, but only give a very detailed list of working conditions. Ideally, policy-makers should be able to have a synthetic indicator.

  In this chapter, we suggest ranking occupations according to their arduousness inferred from how they predict late-years health. The quantification of (relative) arduousness is thus indirect but more in line with the way the concept is defined by job demands and job quality literature (Bakker and Demerouti, 2007; Chen et al., 2017). A more arduous/demanding occupation requires more physical and/or psychological effort/skills and *consumes more physiological and/or psychological resources*. If occupations are unequally stressful or physically demanding, they should contribute to individuals' health gradient. We thus posit that it is via a careful examination of the relationship between health and occupational differences that we should be able to best rank occupations in terms of their arduousness. In

[3]See onetcenter.org.

[4]See eurofound.europa.eu/surveys/european-working-conditions-surveys-ewcs.

this chapter, we ask whether the health status at 50 and beyond could be used to infer a ranking of occupations that is as relevant as those provided by surveys like O*Net or EWC. Detailed data about old age health status are readily available. We use those amassed via the 7$^{\text{th}}$ wave of the Survey on Health, Ageing and Retirement in Europe (SHARE) to analyse the link between health at old age[5] and work history of older individuals in 28 European countries, also available in that survey.

What differentiates our approach from most of the job demands or work-health literature is that we are not just interested in the health consequences of the current or most recent occupation, but the one(s) representing a *career*. That objective directly derives from the recent availability in SHARE of a detailed account (including in terms of occupation) of people's entire careers. As far as we know, ranking occupations in terms of arduousness, from data documenting people's careers and their late-years health is something new in the economic literature.

- The second contribution of the chapter pertains to the quantification of *i)* the degree of career length differentiation required to compensate occupation arduousness and *ii)* the *relative contribution* of career arduousness to the risk of poor health beyond 50,[6] in particular, in comparison with pre-labour market determinants of late-years health that we can control for thanks to the 7$^{\text{th}}$ wave of SHARE. In other words, we do not only assess the impact of career arduousness on health, but also "how much" career arduousness is responsible for differences in health at old age. For that purpose, we use the natural decomposition of the variance, as suggested by Shorrocks (1982). This allows us to quantify the relative importance of career arduousness to health inequality compared to other variables like what epidemiologists call people's health endowment and other *pre-labour-market* entry determinants of late-life health (e.g. education, gender). One of the remarkable features of SHARE is to inform on respondents' initial health endowment before entering the labour market. SHARE collects the health status during teenage years, along with information on whether parents are dead and if so, their age at death. These variables allow us to control for the latter's direct impact on late-life health, but also its potential role on entry-level occupational choice. From an econometric point of view, these represent a source of selection bias. They must be taken into account to better measure the effect of professional occupation on later

[5] SHARE samples respondents from the age of 50.
[6] And by extension, the risk of short life.

health.

The first key result of the chapter is to show that a ranking of career arduousness could indeed be inferred from health at old age and could serve as a reasonable substitute for a detailed arduousness occupational survey. Next, we show that the number of years required to compensate for job arduousness could be quite important. Then, we address the question of the relative contribution of career arduousness to people's health. And we show that career arduousness, although a statistically significant determinant of health in old age, does not emerge as being the main driver of late-years health inequalities. The rest of this chapter is structured as follows. The methods are explained in Section 2.2 and data are described in Section 2.3. Section 2.4 presents the results of ranking occupation arduousness and Section 2.5 those of career length differentiation and variance decomposition. Robustness analysis of our results is done in Section 2.6 and Section 2.7 concludes.

2.2 Methods

This chapter aims to analyse the link between professional occupations and health at older age in order to provide a ranking of job arduousness. Let us consider $Health_{i,j}$, a measure of poor health considered binary and equals to 1 if individual i in country j is in poor health and 0 otherwise. We consider that $Health_{i,j}$ is a function that can be written as follows:

$$Health_{i,j} = \alpha + \beta\, OCC_i + \gamma\, X_i + \delta_j + \epsilon_{i,j} \tag{2.1}$$

where OCC refers to the occupation, X is a vector of controls and δ is the country fixed effect. (2.1) will be estimated separately for men and women. The occupation variable may refer to the main, the first or the last job or the time spent in each occupation (coded at the ISCO 2 digit). We will test those different specifications in order to know if our results depend on them. The vector of controls will also allow us to obtain the impact of occupation on the health net of the impact of the control variables. Those are age, education, father's occupation, initial health endowment and country fixed effects. Our controls do not comprise behaviours that could impact health (e.g. smoking, drinking, diet or the practice of sports). Neither do they compromise income. Hence, the coefficients that we report hereafter should be seen as an upper bound of the "pure" effect of occupation on long-term health. Also, we believe that it is important to assess how much our arduousness coefficients change when we add those controls variables, and it is the reason why we will add them progressively. The assessment is done using a coefficient decomposition "à la Gelbach (2016)". This allows us to identify the key factors driving the gradual reduction of our arduousness estimates when enriching our model; in particular the role of the correlation between the level of pre-labour market endowments (education, father's education and initial health) and the likelihood to exert different occupations. Note that all our models are estimated using OLS instead of logit. This has the advantage of generating coefficients that can be decomposed. We have checked that this does not affect our other key results. Second, we quantify the number of years required to compensate for the job arduousness and ensure that workers can expect to retire in the same health. We compute them by dividing the coefficient of the profession ($\widehat{\beta^{OCC_i}}$) by the one of age ($\widehat{\gamma^{AGE}}$). The first one quantifies the health gap, characterizing OCC_i (compared to the reference occupation) while the second one is the estimate of the effect of one extra year of age on the likelihood to be in poor health.

$$L^{OCC_i} = \frac{\widehat{\beta^{OCC_i}}}{\widehat{\gamma^{AGE}}} \tag{2.2}$$

The computed ratio L^{OCC_i} is the number of years ensuring that OCC_i can expect to retire with the same likelihood of (poor) health as the reference occupation. Third, we provide a variance decomposition in order to analyse the relative importance of some determinants of late-life health (e.g. occupation) versus others (e.g. country). We draw from the method pioneered by Shorrocks (1982) and used by Fields (2003) in labour economics and by Jusot et al. (2013) in health economics. It consists of combining regression analysis with variance decomposition. The procedure consists of two stages. At stage 1, using equation (2.1), we predict the health based on the vector of regressors:

$$\begin{aligned}
\widehat{Health}^{OCC_{i,j}} &= \widehat{\beta^{OCC}} \times OCC_{i,j} \\
\widehat{Health}^{X^k_{i,j}} &= \widehat{\gamma}^k \times X^k_{i,j} \\
\widehat{Health}^{\delta_{i,j}} &= \widehat{\delta}_j
\end{aligned} \tag{2.3}$$

At stage 2, we use the variance of health as a reference to quantify the contribution of each variable. The decomposition is given by the covariance between each regressor and the health outcome.

$$\sigma^2\left(\widehat{Health}_{i,j}\right) = \sigma\left(\widehat{Health}_{i,j}, \widehat{Health}^{OCC}_{i,j}\right) + \sigma\left(\widehat{Health}_{i,j}, \widehat{Health}^{X^k}_{i,j}\right) + \sigma\left(\widehat{Health}_{i,j}, \widehat{Health}^{\delta}_{i,j}\right) \tag{2.4}$$

Therefore, the relative importance of a particular variable (or vector of variables) is the ratio of its covariance divided by the total model-explained variance.

$$ratio^{OCC} = \frac{\sigma\left(\widehat{Health}_{i,j}, \widehat{Health}_{i,j}^{OCC}\right)}{\sigma^2\left(\widehat{Health}_{i,j}\right)} \tag{2.5}$$

We now describe our data before moving to the presentation of our results.

2.3 Data

This chapter uses the 7$^{\text{th}}$ wave of the Survey on Health, Ageing and Retirement in Europe (SHARE). This wave was conducted across 28 European countries[7] and Israel in 2017. The 7$^{\text{th}}$ wave contains several "retrospective" modules, whose aims are to provide detailed data about the respondent's history. The 3$^{\text{rd}}$ wave also contains a retrospective module. However, the occupation variable is only detailed at ISCO-1 digit. Due to this limitation, we only use the 7$^{\text{th}}$ wave. Extensive information is provided about, among others, childhood health and job history. The original sample contains 77 263 observations.

Our main variables of interest are the health at old age, the job history and the childhood conditions. Obviously, it would also be interesting to do the analysis exploiting information on people's lifespan. Unfortunately, this information is not available in SHARE. It is only available for those respondents who died (and for which the follow-up was done rigorously), thus at most 15% of the total pool of respondents.[8] The health variable used is the self-rated health. It is the answer to the question "How would you rate your health?" on a 5-items scale: Excellent, Very Good, Good, Fair and Poor. This variable is known for years to be a reliable indicator of health (see e.g. Bound, 1991; Idler and Benyamini, 1997), physical as well as mental health (Han and Jylha, 2006). It is frequently reassessed with the same conclusion about its validity (see e.g. Schnittker and Bacak, 2014).[9] Following Etilé and Milcent (2006), we dichotomized self-reported health into "Good, Fair and Poor" versus "Excellent and Very good". Moreover, there exists a strong link between this variable and mortality (see e.g. Kaplan and Camacho, 1983; Jylhä, 2009). Table 2.1 details the health variable before having been dichotomized. Descriptive statistics of the sample can

[7]Those countries are Austria, Germany, Sweden, the Netherlands, Spain, Italy, France, Denmark, Greece, Switzerland, Belgium, Czech Republic, Poland, Ireland, Luxembourg, Hungary, Portugal, Slovenia, Estonia, Croatia, Lithuania, Bulgaria, Cyprus, Finland, Latvia, Malta, Romania and Slovakia.

[8]SHARE also asks respondents to gauge their chance of reaching a certain age. Analysing how occupations affect these expectations might be interesting, but it would add the complexity of controlling for the role of the (potentially quite heterogeneous) biases that people have about their longevity.

[9]It is also a good predictor of more elaborate health indices that can be computed using SHARE numerous subjective and objective health items (Vandenberghe, 2020).

be visualized in Table 2.2; for example, the average health of "Food preparations assistants" is worse than the average health of "Teachers". In the 7th wave of SHARE, respondents were asked to retrace their complete job history by providing the starting/ending year of each of their jobs that lasted more than 6 months. Job titles are reported at ISCO-4 digits, which we collapsed into ISCO-2 digits for data issues. We transformed the job history into several variables: the first job, the main job, the last job and the time spent in each ISCO code. We define the main job as the one having spanned the longest. We withdrew observations having as main job: "Commissioned armed officers", "Non-commissioned armed forces officers", "Armed forces occupations, other ranks" and "Street and related sales and services workers" due to the small number of observations from those categories.

One of the strengths of this chapter is that SHARE data allows us to control for the initial health endowment. We are not only able to control for the health status of the individual at age 15, but we can also account for the inherited health endowment. The health status at that age is reported retrospectively by the respondent in five items that we group as a binary variable, as we do with the health outcome at older age. We then proxy inherited health endowment by the death status of the parents. To do so, we consider whether parents are currently alive, and if they have died, we consider whether they "prematurely" died (i.e. they died younger than the median age at death in the considered country) or not. This variable can be considered as a proxy of the "genetic" background of the respondent under the assumption of intergenerational transmission of health (Trannoy et al., 2010). We also control for the father's occupation as a proxy for the socioeconomic conditions in childhood. SHARE data has some limitations. First, they do not include a repeated assessment of health during the job history. This is a limitation if one is interested in exploring the dynamic relationship between the evolution of health and occupational choices (Ravesteijn et al., 2018). However, in this chapter, we care more about the long-term impact of occupation. Second, the participant's history is reported retrospectively and a long time since it happened (i.e. a retiree in 2017 provides his work history since 1970 if he started working at 20). This can lead to memory biases. To reduce this problem, the survey uses a "Life History Calendar" approach to help the respondent to report accurately his history. Third, SHARE data cover several quite different countries that have reached different levels of economic development and have established different health and welfare institutions, where health and safety regulations may exist to a quite variable extent. We posit in this chapter that a significant part of that (unobserved) country-level heterogeneity can be controlled in a pooled analysis using country fixed effects. To increase the inherent flexibility of our econometric modelling, we also conduct some robustness analysis by group of GDP-per-headsimilar countries. But ideally, more should be done to account for the potentially important role of country-specific characteristics affecting both our outcome variable (health) and some of the determinants we care the most about (e.g. occupations). Fourth, we only have data of individuals starting at 50+, which means that we do not consider the distribution of the risk of early death. This is a problem in as much the magnitude of the relative risk of early death of an occupation exceeds (in absolute value) the relative risk of poor health that we observe among survivors. But having to rely on the latter assumption represents a limitation of our study.

2.4 Ranking occupation arduousness

This section details our analysis of the impact of occupation on health. Recall that the goal of this chapter is to provide a *ranking* of occupation arduousness. We have two main concerns. The first is to know if the specification of our variable "occupation" can change our ranking. The second is to know how sensitive our ranking is to the inclusion of control variables. We start our study by analysing the first point. We consider equation (2.1), where OCC refers to the *main job* and X to age. We have chosen "Business and associate professionals" as the reference occupation.[10] The results are displayed numerically in Table 2.3 (male) and 2.4 (female) and graphically in Figure 2.1. The magnitudes of the coefficients show a clear rank with presumably less arduous professions, like "Teaching professionals" being negatively associated with poor health, and more arduous ones like "Refuse and other elementary workers" or "Food preparation assistants", showing the opposite. A sample of 16 occupations over 38 have a significant (at 5 %) coefficient for male and 22 for female. An interesting coefficient is the one corresponding to people who "never worked". For male respondents, it is located in the middle of the figure, suggesting that half of the occupations have a "protective" effect; while others (all those below) have a detrimental effect on health. For female respondents, the "never worked" coefficient is clearly lower suggesting that many more occupations have a "protective" effect. This could be due to the fact that female not working do more home chores and this has a detrimental effect on their long-term health. We have examined further the composition of the "never worked" respondents. It turns out that they are slightly less educated and that many females who never worked are from Italy or Spain. Turning now to the age coefficient, we see that being older is indeed associated with a higher probability of being in bad health.

[10]The reason being that it is the most frequent occupation in our sample.

However, those coefficients could be biased due to a mixture of measurement error and selection problems regularly highlighted by people doing occupational cohort studies. Measurement error could be driven by the main job dummy being a poor proxy of the actual exposure to arduousness, in particular its duration. Also, individuals move from job to job in a non-random way (e.g. the choice of a less arduous main job could be a response to the health deterioration caused by a first job that was particularly arduous). We will discuss endogeneity issues more thoroughly below (see Section 2.4.1). In short, to assess the magnitude of these potential biases, we re-estimate (2.1) with alternative specifications of our occupation variable OCC. Figure 2.2 (male) and Figure 2.3 (female) show the correlation between our previous results (main job) and the results, where OCC refers to the *time spent* working in each ISCO code. The rank is stable across the two and the Spearman correlation coefficients are 96.42 % for male and 92.81 % for female. We use the Spearman correlation (instead of the Pearson one) because we want to assess the stability of a rank (and not of an absolute value). We have also tested the robustness of our ranking by computing (2.1) with *first* or *last job* as the independent variable. As could be seen in Figure 2.4 (male) and Figure 2.5 (female), all coefficients follow the same trend. The Spearman correlation between those of the main job and those of the first job is 82.51 % for male and 85.49% for female; the one between the main job and the last job is 93.08 % for male and 96.56 % for female. Still, this does not mean that our coefficients are free from potential biases. However, the goal of this section is to focus on ranking occupations and this shows that our ranking is stable, whatever the occupation variable used is.

We now analyse if adding new variables of control changes the ranking of occupations arduousness. We have recomputed (2.1) and added education in Model 2 along with initial health endowment and father's occupation in Model 3. The results are displayed in columns 2 and 3 of Table 2.3 (male) and of Table 2.4 (female). The reference level for education is post-secondary, non-tertiary education ($ISCED\,4$). The education variable has the expected sign. A higher level of education increased the likelihood of being in good health. The overall magnitude of occupation coefficients fall by around 25 % for male and 45 % for female, but remain significant in explaining health status. Turning now to the last regression, we see that being in poor health during teenage years increases the probability of reporting poor health beyond 50. Similarly, having a parent who died prematurely is associated with a higher probability of being in poor health in old age compared to having parents still alive. The father's occupation is not significant, except for the woman who had a father who was a "Senior managers and professionals", which decreases the probability of being in poor health (compared to "Office clerks, service workers and sales workers"). The coefficients associated with professional occupations remain significant with only a slight decrease compared to the second specification. The coefficients of the different occupations across the regressions can be visualized in Figure 2.6 (male) and 2.7 (female). The ranking is stable across regressions and we have a Spearman correlation of 93.49 % between the Model 1 and Model 2 for male (95.38 % for female) and of 93.06 % between the Model 1 and Model 3 for male (93.25 % for female). This shows that we can reasonably infer a ranking of occupation arduousness from data on poor health above 50. The reduction of the coefficients that we find here is lower than the one found by Ravesteijn et al. (2018) (-60%). This difference could be explained by the fact that Ravesteijn et al. (2018) controlled for one-year lagged health while we control for initial health endowment during adolescence. Both control strategies have their pros and cons. Controlling for health a year before withdraw a potential bias; however, it cannot control for the long-lasting effect of one's occupation on health. The reverse applies when we control for health during the adolescence.

2.4.1 Endogeneity concerns

The first focus of this chapter was to rank professions based on their arduousness. This does not demand that our coefficients are unbiased as long as the bias is in the same direction for all coefficients. We have shown that changing the specification of the occupation variable or adding new control variables does not change our ranking. Nevertheless, some of the other results presented hereafter depend on our capacity to deliver unbiased estimates. We will first compute the number of years required to compensate for job arduousness. This is done by dividing one coefficient by another. Then, we will do a variance decomposition. In both cases, it is desirable that our coefficients are the least biased. Establishing an unbiased estimate of the impact of occupation on health is challenging. In addition to the measurement errors discussed above, there are several endogeneity concerns. First, health at entry in the labour market could affect the choice of the first job. Second, the deterioration of health during the career (health shocks) could lead people to abandon more arduous occupations (this is known as the simultaneity/reverse causality bias or as the “healthy worker bias” in health economics). Third, other unaccounted factors (e.g. unobserved heterogeneity in terms of risk preferences) can affect both health and occupational choice. The literature always struggles to cope with either of these problems. It is challenging to find a plausible exogenous variation of occupations - even if they are simply dichotomized between blue and white collar.

In this chapter, we are not able to address fully the unobserved heterogeneity problem, but we believe we have a good chance of addressing the two other sources of endogeneity. First, we control for health at 15 and both parents' longevity. Note that we control for health *during the adolescence*, hence before the choice of an occupation and the *entry in the labour market*. Moreover, parents' longevity and vital status permit to us to proxy the inherited part of people's initial health endowment, and we also control for father's occupation to proxy the socioeconomic childhood conditions. As to the simultaneity problem, it is important to stress that we consider the impact of past occupation on health beyond 50. This means that there is a potentially important lag between the moment of exposure to a certain degree of job arduousness and the moment health is assessed. By construction, this eliminates to a large extent the risk of simultaneity bias. Moreover, we use the job arduousness of the *main* job (defined as the longest spell). If we make the reasonable assumption that the other (shorter) job spells are more likely to correspond to responses to health shocks, this also contributes to limiting the risk of simultaneity/reverse causality.

As an extension to the discussion above, we have performed a decomposition "à la Gelbach (2016)". As such, this decomposition does not represent an additional answer to endogeneity concerns. What it does is to show the impact of the inclusion of pre-labour market entry variables on our estimates of arduousness, in particular that of their non-inclusion in the econometric model would lead to an overestimation of arduousness. Gelbach reminds us of what are the two key determinants of the evolution of a coefficient of interest (here a series of coefficients $\widehat{\beta^{OCC}}$ capturing the link between an occupation and health beyond 50) when adding to the initial model a series of controls X_k (education, initial health endowment), see Figure 2.6 and 2.7. Gelbach refers to the baseline $[b]$ vs. full $[f]$ model (i.e. the one with education and health endowment controls in our case). He shows that:

$$\begin{gathered}\widehat{\beta_b^{OCC}} = \widehat{\beta_f^{OCC}} + \sum_k \delta^{X_k} \\ \text{where } \delta^{X_k} = \widehat{\rho^{X_k}}\ \widehat{\gamma^{X_k}}\end{gathered} \tag{2.6}$$

and where $\widehat{\gamma^{X_k}}$ represents the impact of variable X_k on health beyond 50 and $\widehat{\rho^{X_k}}$ the link between X_k and occupation OCC. In technical terms, $\widehat{\rho^{X_k}}$ is the outcome of the OLS regression of X_k on OCC. Note also that as we are dealing with occupation dummies, everything in terms ρ_k^X is to be interpreted as deviation from what happens with the reference occupation. The point is that the two determinants of the reduction of the magnitude of our arduousness coefficients (25% for males and 45% for females) visible in Figure 2.6 and 2.7 are: *i)* the propensity of our pre-labour endowment variables (education, initial health endowment) to impact health beyond the age of 50 $(\widehat{\rho^{X_k}})$ and, also, *ii)* the propensity of people exerting different occupations to vary in terms of the level of these pre-labour entry endowment variables ($\widehat{\rho^{X_k}}$).

The full list of δ^{X_k} delivered by the Gelbach decomposition is reported in Table 2.5 (male) and in Table 2.6 (female). There is one by control variable $\times$ the number of occupations. To illustrate the outcome of the decomposition of the δ's suggested by (2.6), consider education (*Education*) as control, and two a priori contrasted occupations: "Food preparation assistants" and "Chief Executives, senior officials and legislators". Recall that our reference profession is "Business and associate professionals". Table 2.5 shows that $\delta^{Education}$ is .01158 for (male) "Food preparation assistants" and -.01528 for "Chief Executives, senior officials and legislators". We know that these numbers combine *i)* the (negative) contribution of education to the risk of being in poor health[11] and *ii)* the propensity of these occupations to be associated with (low/high) educational attainment (relative to the reference occupation). As the vector of γ's is the **same** for the two occupations, the different δ's we have can only come from differences in terms of ρ's. As we would expect, the implicit ρ is positive for "Chief Executives, senior officials and legislators" (i.e. they have higher educational attainment than the reference occupation, and in (2.6), this translates by the β from the "full" model to be less than the one from the "baseline" model), whereas the implicit ρ is negative for "Food preparation assistants" (i.e. they have lower educational attainment than the reference occupation and, in (2.6), we have that the "full" model delivers a β that is less negative than the "baseline" model). See Section 2.8 for the detailed decomposition of $\delta^{Education}$ as crossproduct of ρ's and δ's.

2.4.2 Country analysis

The last analysis that we performed is to know if our ranking is stable across countries. SHARE contains observations from several countries and same-titled occupations could correspond to quite different degrees of arduousness, depending on the country in which they have been exerted. So far we have posited that those differences are taken into account by the country fixed effect (δ_j). To relax this assumption, we have split the countries into three groups depending on their GDP per capita.[12] The ranking of occupations is not stable across groups. The Spearman correlation is only 16,09% between high and middle countries

[11] The reported γ's for education in Table 2.3 and 2.4 confirm that education's contribution is negative.

[12] We group countries as follows. High: Austria, Germany, Sweden, The Netherlands, France, Denmark, Switzerland, Belgium, Ireland, Luxembourg, Finland and Israel. Middle: Spain, Italy, Czech Republic, Portugal, Cyprus, Malta, Slovenia and Estonia. Low: Poland, Hungary, Croatia, Lithuania, Bulgaria, Latvia, Romania, Slovakia and Greece.

for male and 5,97% between high and low. The figures are 29,4% and 29,34% for female. However, the rankings are stable across regressions inside each country group (see Table 2.7). This means that policy-makers should favour rankings that are based, as much as possible, on country-specific microdata. And if they use data from several countries, they should try as much as possible to pool data coming from countries similar in terms of GDP per capita.

2.5 Career length differentiation and variance decomposition

The first objective of this chapter was to use late-years health data to rank career main occupations in terms of their arduousness. There are two other questions that we address in this chapter. First, the degree of career length differentiation that would be necessary to the equalisation of (expected) health at the moment of retirement. Second, the relative contribution of occupation arduousness to late-years health. This is an important question because the career length debate often focuses exclusively on working conditions. However, there are not the only factors affecting health and policy-makers should have an idea of the relative contribution of pre-labour market entry determinants of poor health (e.g. education, inherited health endowment...) vs. that of working conditions and occupational arduousness. The larger the contribution of childhood or inherited determinants, the more relevant it would be to develop policies targeting the early years of life, alongside those accounting for labour/occupation-related health inequalities. Let us first analyse the difference of career length required to compensate workers for job arduousness.

2.5.1 Differences of career length

To estimate the degree of differentiation required (i.e. the difference in terms of years spent working compared to the reference occupation), we considered (2.1) where OCC refers to the main job and X to age, education, father's education and initial health endowment. We use (2.2) to compute the career length of each job. The coefficient of the occupation i (β^{OCC_i}) measures poor health risk gap (compared to the reference occupation) beyond 50. The coefficient of age (γ^{AGE}) measures the impact of one more year on the incidence of that risk. Results are shown in Table 2.8 for male and Table 2.9 for female. Column 1 is the result where we take the upper bound of the 95 % confidence interval of the age coefficient, Column 2 is the result where we take the age coefficient and Column 3 is the result where we take the lower bound of the confidence interval. We have done those three columns because one can say that the passage of time is not the same across professions and that ageing in a more harmful profession could be harder than in a lower one. Two results emerge from those tables. First, the spread of career length is lower for female than for male. Second, the spread is quite huge. Setting aside the first three extreme values, we see that the spread is around 15 years. “Drivers and mobile plant operators” (male) should have a career length cut by 11.07 years compared to the reference one (i.e. “ Business and associate professionals”) and “Numerical and material recording clerks” (male) should add 2.99 years to the regular career length. This means that compensating for job arduousness could entail large differences of career length. The estimations heavily depend on the value of the denominator. Two limits should be mentioned to this calculus. First, the impact of age may change over lifetime. Computing γ^{AGE} over a sample of 50+ or 70+ could not give exactly the same results. Second, the age coefficient is a derivative which means that it is a *marginal* change. Using a marginal change to compute a career length differentiation of up to 15 years is not fully adequate. So, those estimations are more a first back-of-the-enveloppe calculus than a thorough scientific one.

2.5.2 Variance decomposition

Let us now turn to the variance decomposition. We analyse this point by considering (2.1), where OCC refers to the main job and X to age, education, father’s education and initial health endowment. The method used is described in Section 2.2 and the results are reported in Table 2.10 (male) and Table 2.11 (female). The table is split in four columns. “All”, “high”, “middle”, “low”; which refers to all the countries and to the country groups (based on their GDP per capita) used before. First of all, we see that occupation is a minor contributor of poor health (7.07 % for male and 4.06 % for female). The two most important variables are countries and initial health endowment. Decomposing by group of countries, we see that occupations are more important in richer countries. Nevertheless, it is still a relative minor contributor compared to the initial health endowment. This underlines that the debate on job arduousness is important, but cannot ignore the importance of initial health endowment when designing policies.

2.6 Robustness

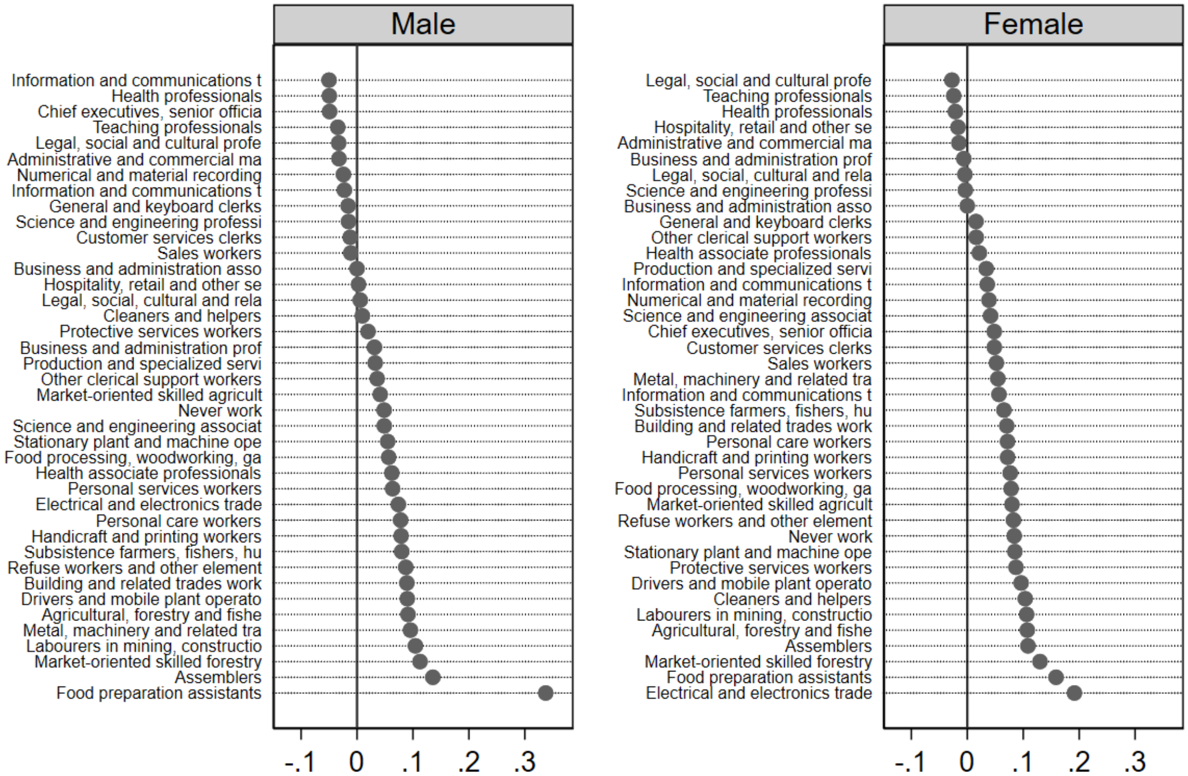
As robustness checks, we have considered two different tests. First, we have re-estimated our model considering a truncated sample where we withdrew individuals aged above 70.

This new sample restricted the analysis to people at or close to working age. Second, we have re-run our model using another health indicator than self-assessed health. The new indicator is based on a principal component analysis of a set of health indicators, namely self-rated health, long-term illness, limitation in daily activities, number of limitations and limited with instrumental activities of daily living. Results are displayed in Table 2.12 and 2.13 (male) and in Table 2.14 and 2.15 (female). The new estimated coefficients are very correlated with our previous results and the professional occupation remains a relatively minor determinant of poor health.

2.7 Conclusion

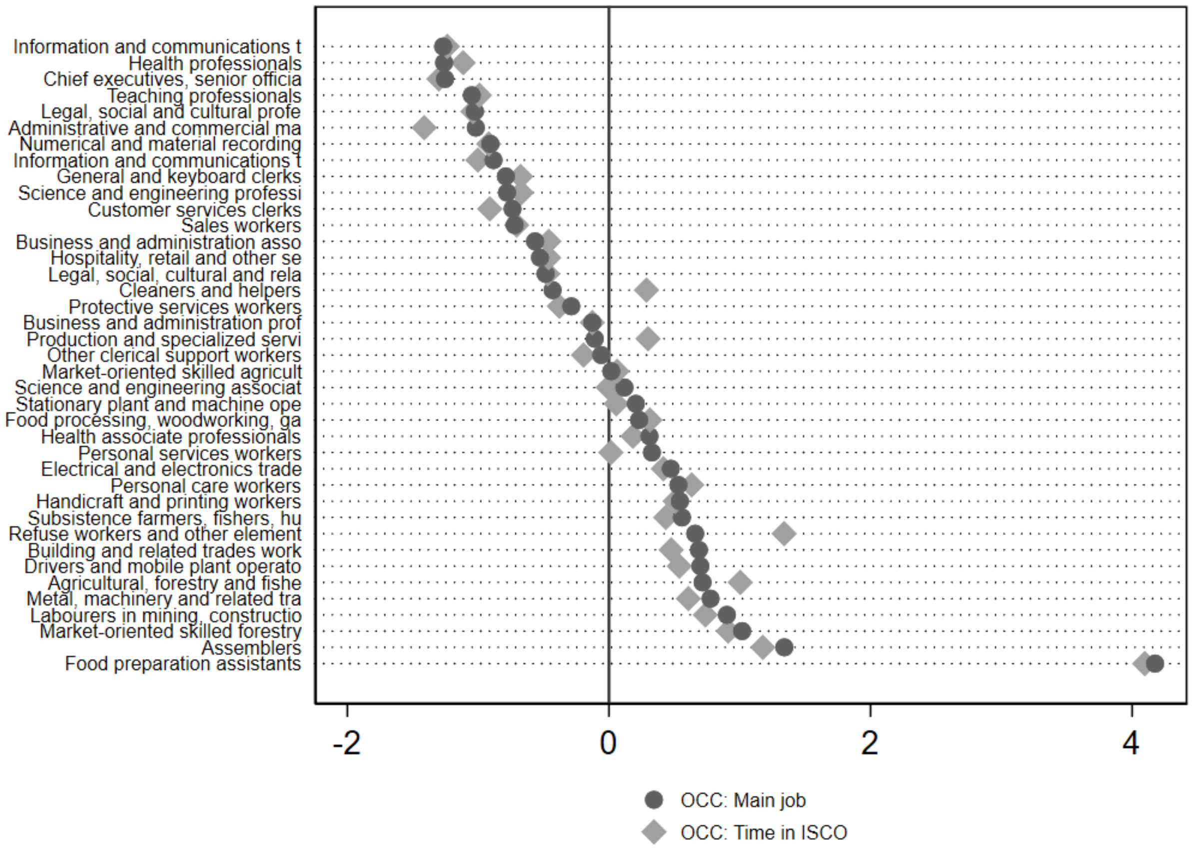
The first objective of this chapter was to assess the possibility to rank occupations in terms of their arduousness using microdata on health beyond the age of 50 instead of "direct" measure of arduousness provided by surveys describing working conditions by occupation. The results show that it is indeed possible to rank using data that are readily available from health and retirement surveys like SHARE that comprise job history modules. We have shown that the ranking is robust to different specifications of the occupation variable as well as the inclusion of different controls, in particular pre-labour-market-entry variables (education, father's occupation and initial health endowment). We have shown that the ranking should be done preferably within homogeneous countries (in terms of GDP per capita). Then, we have estimated the degree of career length differentiation required to compensate for the arduousness. We have shown that the degree of differentiation could represent up to 15 years of difference between the least and most arduous occupations. At the end, taking a global perspective, we have shown that whilst occupation arduousness is a significant contributor to poor health at later age, it is still (quantitatively) a minor determinant. Initial health endowment (proxied here by teenage health and the longevity of the respondent's parents) and country fixed effects (that presumably capture GDP per capita differences) explain a larger part of health differences *ceteris paribus*. One limit of our study is the impossibility to account for the relationship between occupations and the distribution of the risk of death before the age of 50.

In policy terms, our findings provide justification to policy-makers wishing to differentiate pension policy based on people's career. Occupations vary in terms of arduousness and, furthermore, it is possible to rank them ex-ante using readily available microdata. At the same time, the research underlines the importance for late-years health of other early life and pre-labour determinants than are not occupation arduousness. And these comprise people's initial health endowment. This result calls for further research, but in policy terms, it tentatively suggests that compensating individuals for poor health (and by extension longevity differences) calls for more than career length differentiation. It probably requires very early-stage interventions targeting childhood health inequalities, via public health and related policies.



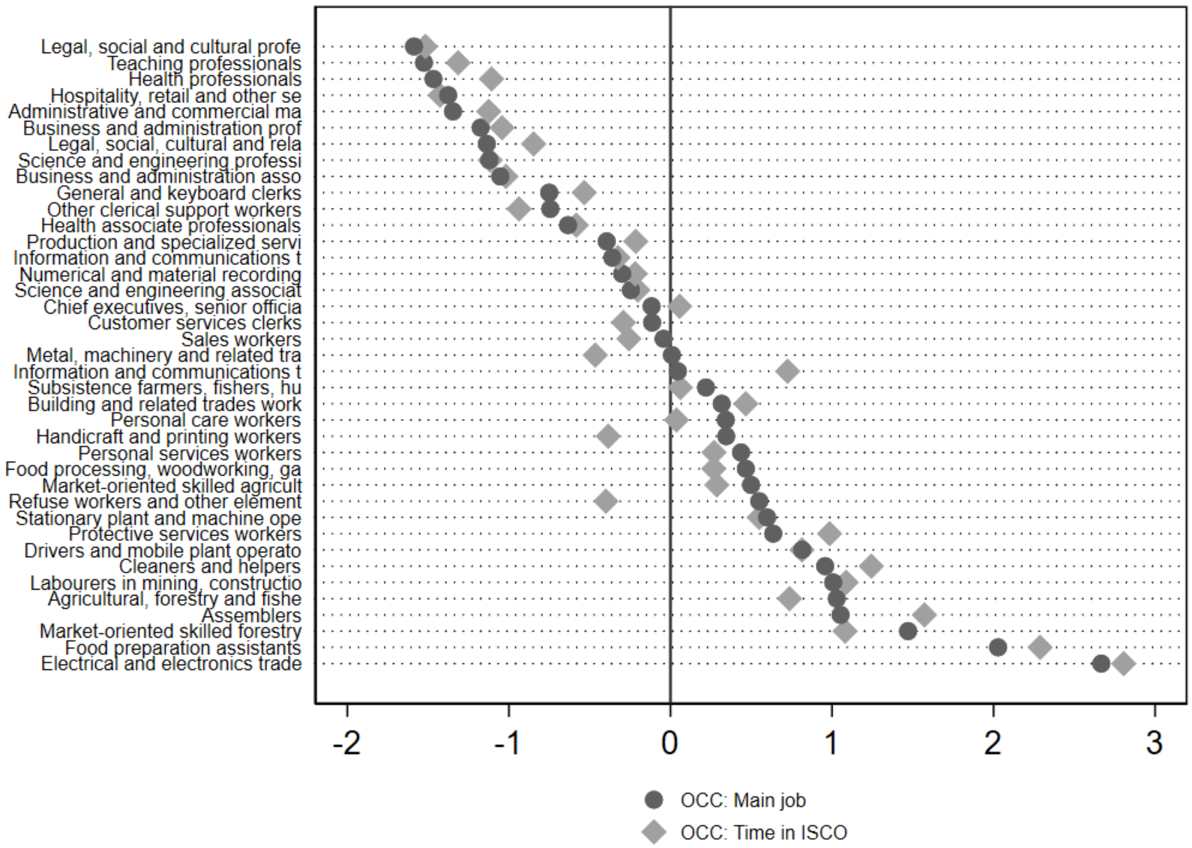
The figure shows the coefficient of the regression (2.1) with main job as the occupation variable controlling for age and country fixed effects. Data are from the 7$^{\text{th}}$ wave of the SHARE survey after dropping incomplete data for the full specification.

Figure 2.1: Regression coefficients by sex between jobs and poor health



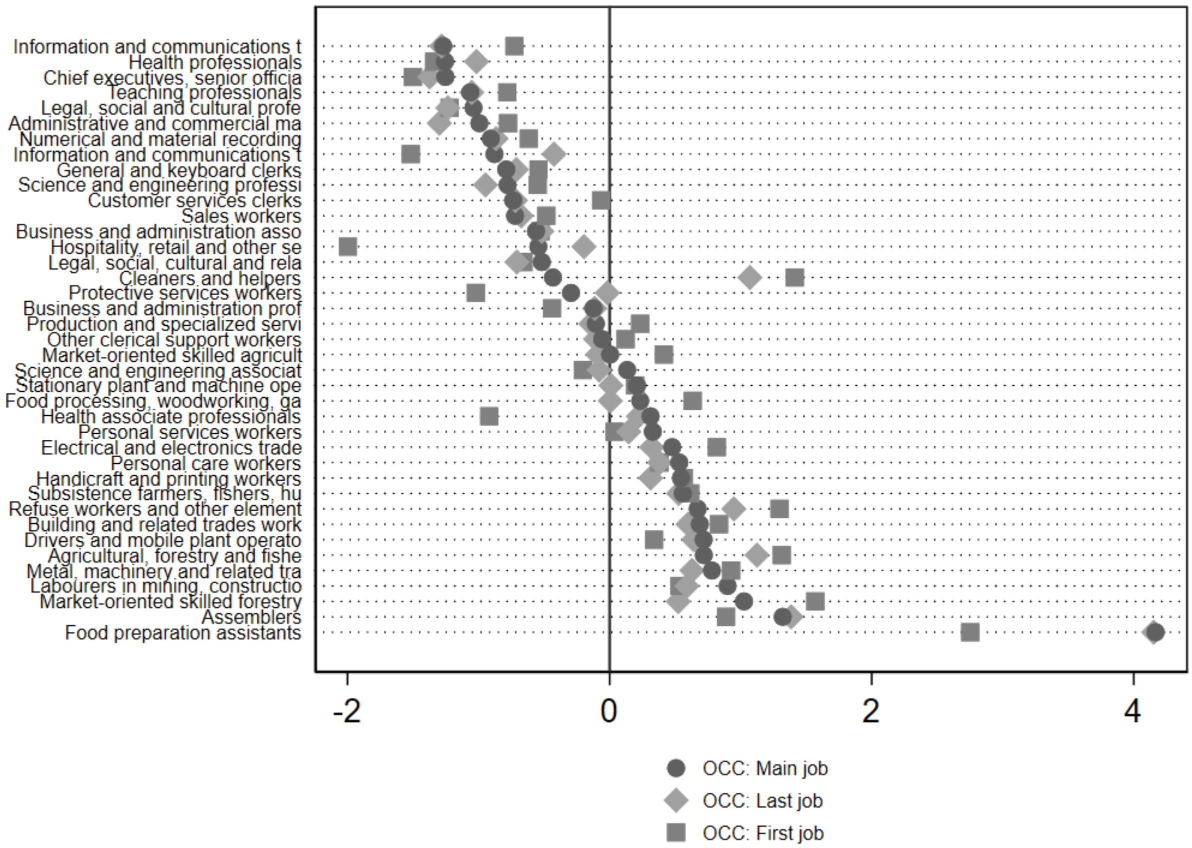
The figure shows the correlation of the coefficients of the regression (2.1) with main job or time in each ISCO code as the occupation variable controlling for age and country fixed effects. Data are from the 7$^{\text{th}}$ wave of the SHARE survey after dropping incomplete data for the full specification.

Figure 2.2: Correlation between coefficients (standardized) with main job and time in each ISCO code as independent variable - Male



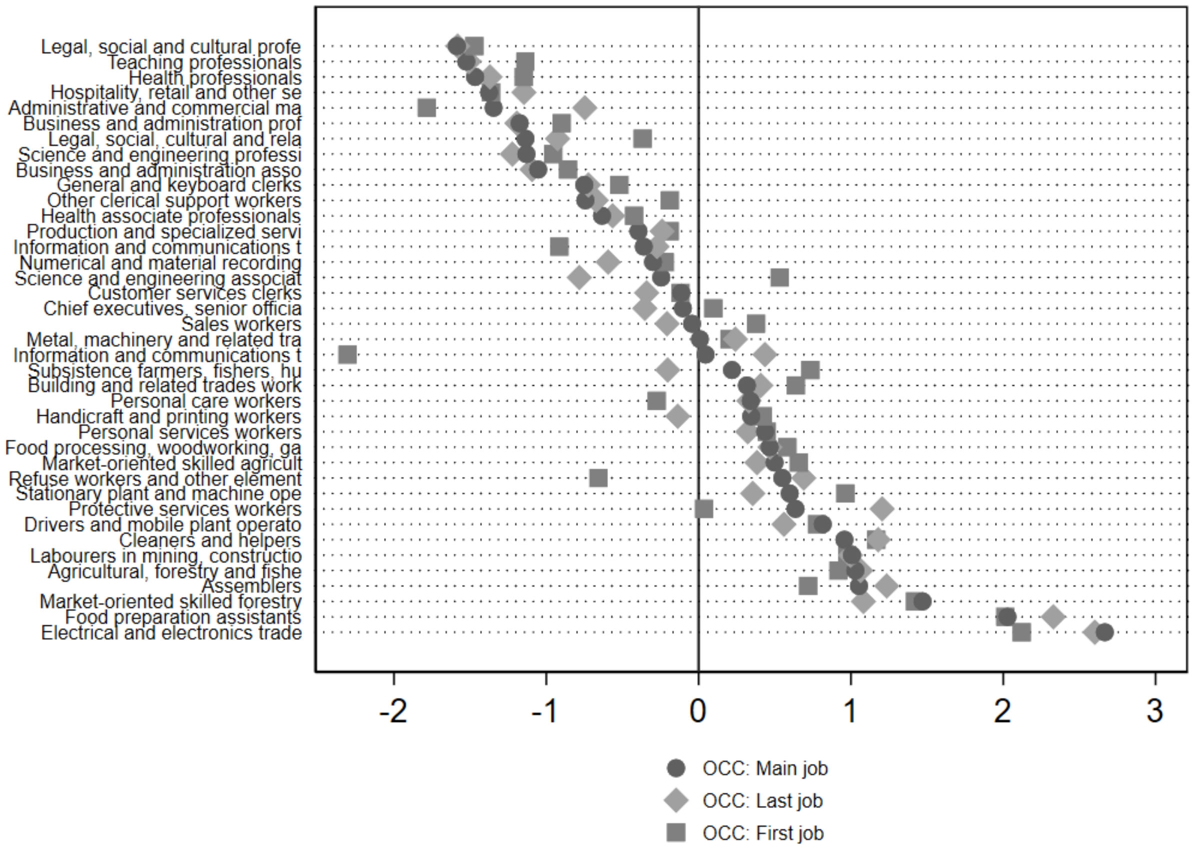
The figure shows the correlation of the coefficients of the regression (2.1) with main job or time in each ISCO code as the occupation variable controlling for age and country fixed effects. Data are from the 7$^{\text{th}}$ wave of the SHARE survey after dropping incomplete data for the full specification.

Figure 2.3: Correlation between coefficients (standardized) with main job and time in each ISCO code as independent variable - Female



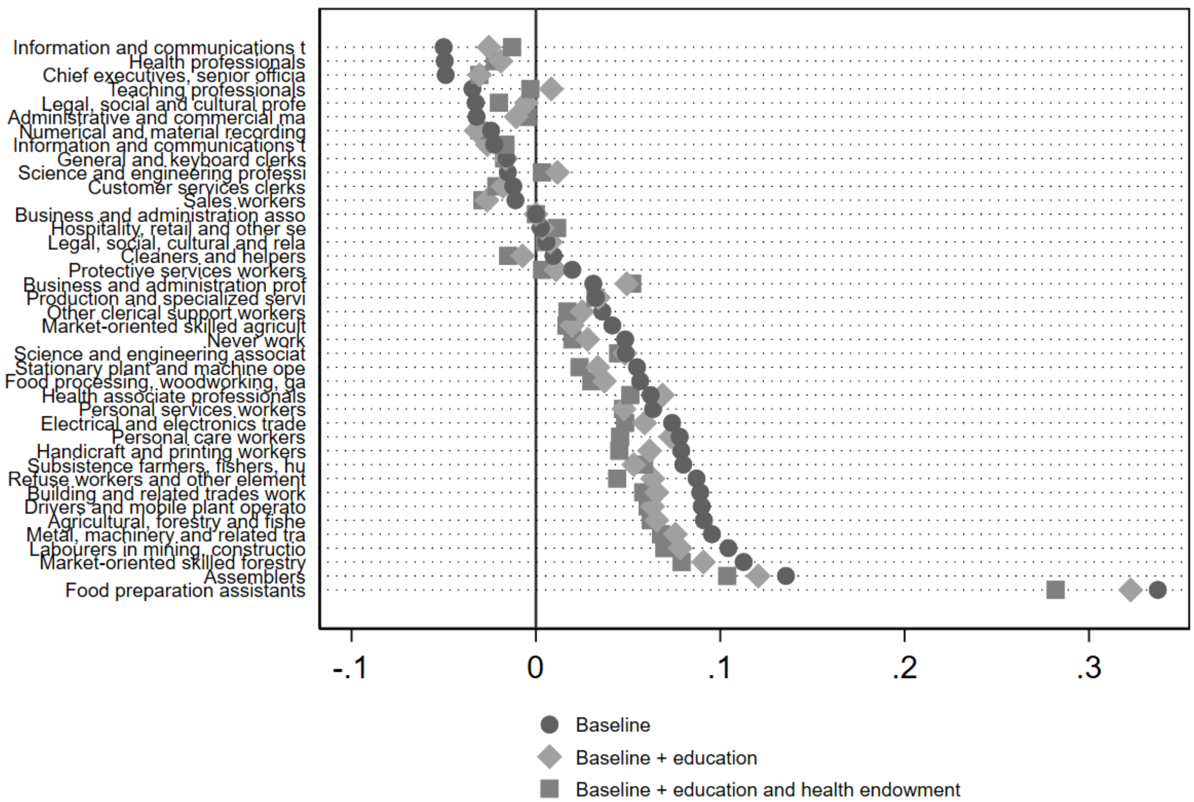
The figure shows the correlation of the coefficients of the regression (2.1) with main job, first job or last job as the occupation variable controlling for age and country fixed effects. Data are from the 7$^{\text{th}}$ wave of the SHARE survey after dropping incomplete data for the full specification.

Figure 2.4: Correlation between coefficients (standardized) with first, main and last job as independent variable - Male



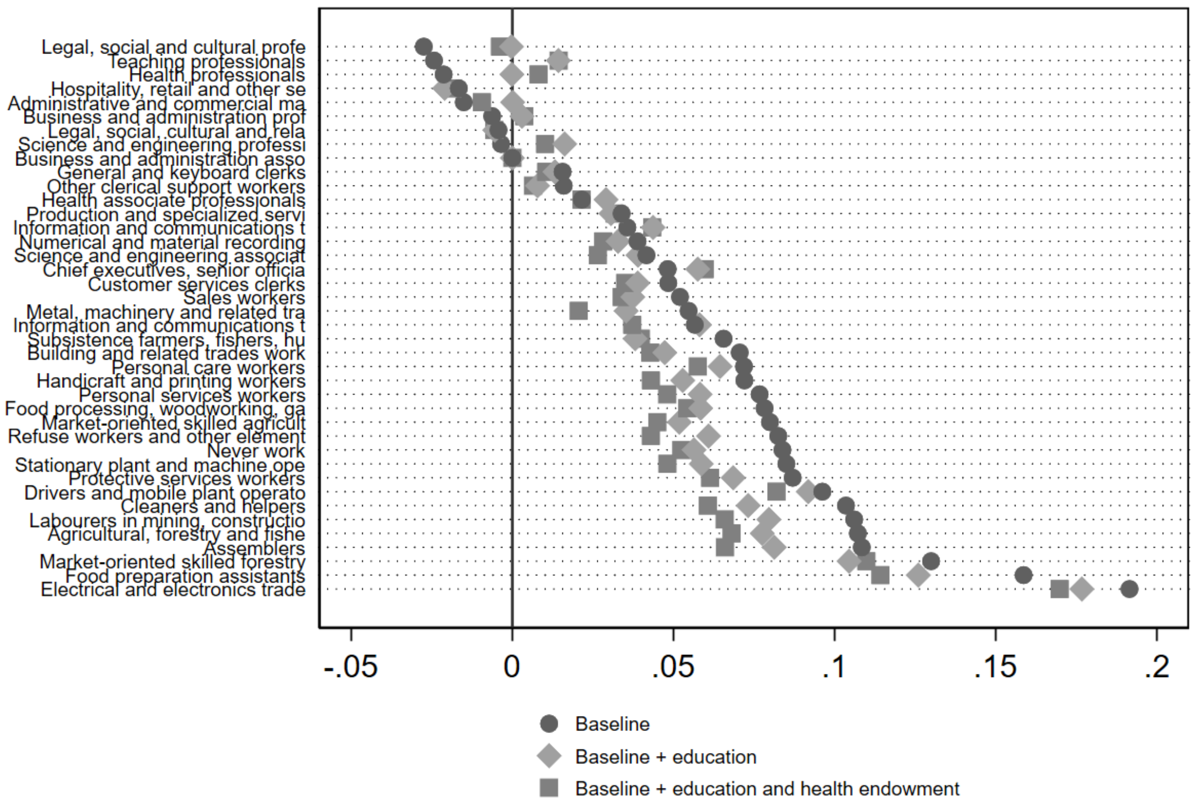
The figure shows the correlation of the coefficients of the regression (2.1) with main job, first job or last job as the occupation variable controlling for age and country fixed effects. Data are from the 7th wave of the SHARE survey after dropping incomplete data for the full specification.

Figure 2.5: Correlation between coefficients (standardized) with first, main and last job as independent variable - Female



The figure shows the correlation of the coefficients of the regression (2.1) with main job as the occupation variable controlling for 1) age and country fixed effects 2) age and education and country fixed effects 3) age, education, childhood variables and country fixed effects. Data are from the 7$^{\text{th}}$ wave of the SHARE survey after dropping incomplete data for the full specification.

Figure 2.6: Reduction of the coefficients across the different regressions - Male



The figure shows the correlation of the coefficients of the regression (2.1) with main job as the occupation variable controlling for 1) age and country fixed effects 2) age and education and country fixed effects 3) age, education, childhood variables and country fixed effects. Data are from the 7th wave of the SHARE survey after dropping incomplete data for the full specification.

Figure 2.7: Reduction of the coefficients across the different regressions - Female

Table 2.1: Health statistics

	Observations	Percent
Excellent	3058	6.11 %
Very Good	7745	15.49 %
Good	18212	36.42 %
Fair	14690	29.37 %
Poor	6307	12.61 %
N	50 012	

Table 2.2: Descriptive statistics

Main job	Obs	Prop Male	Mean age	Mean health	Mean education
Chief executives, senior officials and legislators	679	.69	67.86	.74	3.94
Administrative and commercials managers	568	.52	66.51	.68	4.08
Production and specialized services managers	678	.59	69.02	.77	3.39
Hospitality, retail and other services managers	321	.51	66.74	.74	3.26
Science and engineering professionals	1566	.67	68.25	.74	4.17
Health professionals	1496	.21	65.61	.70	4.16
Teaching professionals	2960	.28	66.93	.70	4.64
Business and administration professionals	831	.35	66.14	.75	3.78
Information and communications technology professionals	356	.54	64.32	.67	4.03
Legal, social and cultural professionals	1105	.35	66.21	.70	4.26
Science and engineering associate professionals	1890	.71	67.59	.79	3.29
Health associate professionals	727	.23	66.20	.76	3.64
Business and administration associate professionals	2556	.36	66.71	.73	3.30
Legal, social, cultural and related associate professionals	458	.38	65.14	.73	3.33
Information and communications technicians	192	.70	66.07	.74	3.47
General and keyboard clerks	2350	.21	66.16	.71	3.18
Customer services clerks	652	.26	66.58	.76	2.98
Numerical and material recording clerks	1177	.30	66.99	.78	3.03
Other clerical support workers	790	.33	65.97	.76	2.96
Personal services workers	1934	.25	65.70	.80	2.57
Sales workers	2518	.24	65.82	.77	2.63
Personal care workers	1375	.06	64.87	.77	2.99
Protective services workers	573	.78	66.21	.75	2.88
Market-oriented skilled agricultural workers	1268	.46	70.87	.84	1.96
Market-oriented skilled forestry, fishery and hunting workers	284	.68	67.93	.85	2.35
Subsistence farmers, fishers, hunters and gatherers	782	.46	67.83	.90	2.20
Building and related trades workers					

(excluding electricians)	2120	.90	66.56	.82	2.35
Metal, machinery and related trades workers	2281	.90	66.81	.83	2.68
Handicraft and printing workers	712	.45	68.43	.83	2.48
Electrical and electronics trades workers	823	.90	66.19	.81	2.96
Food processing, woodworking, garment and other craft and related trades workers	2219	.31	67.19	.83	2.42
Stationary plant and machine operators	1727	.45	67.17	.84	2.29
Assemblers	341	.52	66.24	.85	2.49
Drivers and mobile plant operators	2093	.91	67.00	.85	2.54
Cleaners and helpers	1342	.04	66.72	.84	1.82
Agricultural, forestry and fishery labourers	391	.36	70.85	.88	1.86
Labourers in mining, construction, manufacturing and transport	1523	.56	66.58	.84	2.20
Food preparation assistants	257	.04	66.92	.91	2.035
Refuse workers and other elementary workers	365	.53	66.91	.85	2.46
Never work	3732	.11	70.56	.82	1.65
N	50 012				

The data are from the SHARE Wave 7. Mean age (resp. health) refers to the mean age (resp. health) at the time of the interview. Health equals to 1 means that the individual is in less than very good health. Mean education is the mean of the ISCED code (0 to 6).

Table 2.3: Regression coefficients - Male

	(1) Model 1	(2) Model 2	(3) Model 3
Age	0.008***	0.008***	0.006***
	(0.000)	(0.000)	(0.000)
Chief executives, senior officials and legislators	-0.049*	-0.031	-0.031
	(0.027)	(0.027)	(0.027)
Administrative and commercial managers	-0.032	-0.011	-0.005
	(0.031)	(0.031)	(0.030)
Production and specialized services managers	0.032	0.034	0.032
	(0.028)	(0.028)	(0.027)
Hospitality, retail and other services managers	0.003	0.004	0.011
	(0.039)	(0.039)	(0.038)
Science and engineering professionals	-0.015	0.012	0.003
	(0.021)	(0.022)	(0.021)
Health professionals	-0.049*	-0.019	-0.022
	(0.030)	(0.030)	(0.030)
Teaching professionals	-0.034	0.008	-0.003
	(0.022)	(0.023)	(0.022)
Business and administration professionals	0.031	0.049	0.052*
	(0.032)	(0.032)	(0.031)
Information and communications technology professionals	-0.050	-0.025	-0.013
	(0.036)	(0.036)	(0.036)
Legal, social and cultural professionals	-0.033	-0.005	-0.020
	(0.029)	(0.029)	(0.028)
Science and engineering associate professionals	0.049**	0.048**	0.045**
	(0.020)	(0.020)	(0.020)
Health associate professionals	0.062*	0.069*	0.051
	(0.038)	(0.038)	(0.037)
Legal, social, cultural and related associate professionals	0.006	0.008	0.005
	(0.038)	(0.038)	(0.037)
Information and communications technicians	-0.023	-0.026	-0.017
	(0.043)	(0.043)	(0.042)

General and keyboard clerks	-0.016	-0.016	-0.017
	(0.026)	(0.026)	(0.026)
Customer services clerks	-0.012	-0.018	-0.021
	(0.037)	(0.037)	(0.036)
Numerical and material recording clerks	-0.024	-0.032	-0.031
	(0.030)	(0.030)	(0.029)
Other clerical support workers	0.036	0.025	0.017
	(0.034)	(0.034)	(0.033)
Personal services workers	0.064**	0.048*	0.047*
	(0.027)	(0.027)	(0.026)
Sales workers	-0.011	-0.027	-0.029
	(0.025)	(0.025)	(0.025)
Personal care workers	0.078	0.073	0.046
	(0.056)	(0.056)	(0.055)
Protective services workers	0.020	0.011	0.003
	(0.028)	(0.028)	(0.027)
Market-oriented skilled agricultural workers	0.041*	0.020	0.017
	(0.025)	(0.026)	(0.025)
Market-oriented skilled forestry, fishery and hunting workers	0.113***	0.091**	0.079**
	(0.038)	(0.038)	(0.037)
Subsistence farmers, fishers, hunters and gatherers	0.080***	0.053*	0.059**
	(0.029)	(0.029)	(0.029)
Building and related trades workers (excluding electricians)	0.089***	0.066***	0.058***
	(0.019)	(0.019)	(0.019)
Metal, machinery and related trades workers	0.095***	0.076***	0.068***
	(0.019)	(0.019)	(0.019)
Handicraft and printing workers	0.079***	0.062**	0.045
	(0.031)	(0.031)	(0.030)
Electrical and electronics trades workers	0.074***	0.059***	0.048**
	(0.023)	(0.023)	(0.023)
Food processing, woodworking, garment and other craft and related trades workers	0.057**	0.037	0.030
	(0.024)	(0.024)	(0.024)
Stationary plant and machine operators	0.055**	0.034	0.024

	(0.023)	(0.023)	(0.023)
Assemblers	0.136***	0.121***	0.104***
	(0.039)	(0.039)	(0.038)
Drivers and mobile plant operators	0.090***	0.063***	0.061***
	(0.019)	(0.020)	(0.019)
Cleaners and helpers	0.010	-0.007	-0.015
	(0.075)	(0.075)	(0.074)
Agricultural, forestry and fishery labourers	0.091**	0.066	0.062
	(0.044)	(0.044)	(0.043)
Labourers in mining, construction, manufacturing and transport	0.104***	0.078***	0.070***
	(0.023)	(0.023)	(0.022)
Food preparation assistants	0.337**	0.323**	0.282*
	(0.151)	(0.151)	(0.148)
Refuse workers and other elementary workers	0.087**	0.063*	0.044
	(0.038)	(0.038)	(0.038)
Never work	0.048*	0.028	0.020
	(0.030)	(0.030)	(0.029)
ISCED 0		0.029	0.022
		(0.024)	(0.023)
ISCED 1		0.038**	0.026
		(0.018)	(0.018)
ISCED 2		0.034**	0.029*
		(0.017)	(0.017)
ISCED 3		0.011	0.009
		(0.015)	(0.015)
ISCED 5		-0.057***	-0.046***
		(0.016)	(0.016)
ISCED 6		-0.124***	-0.113***
		(0.034)	(0.034)
Health childhood			0.162***
			(0.007)
Father: Premature dead			0.088***
			(0.012)
Father: Normal dead			0.072***
			(0.012)

Mother: Premature dead			0.025***
			(0.010)
Mother: Normal dead			0.017*
			(0.010)
Father profession:			
Senior managers and professionals			-0.003
			(0.013)
Technicians and associate professionals and armed forces			-0.028*
			(0.015)
Skilled agricultural and fishery workers			-0.003
			(0.013)
Craftsmen and skilled workers			0.006
			(0.012)
Elementary occupations and unskilled workers			0.006
			(0.013)
Unknown			-0.002
			(0.014)
_cons	0.135***	0.171***	0.150***
	(0.033)	(0.036)	(0.037)
N	15 221	15 221	15 221
R^2	11.30 %	12.15 %	15.77 %

The table shows the result of regression (2.1), where OCC refers to the main job. Model 1 includes age in the control variables, Model 2 adds education and Model 3 the childhood circumstances. Our coefficients are reduced when we include more control variables. The job coefficients show a clear gradient with low-arduous occupations, like "Teachers", and high arduous occupations, like "Refuse workers". Standard errors are in parentheses; *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

Table 2.4: Regression coefficients - Female

	(1) Model 1	(2) Model 2	(3) Model 3
Age	0.008***	0.008***	0.006***
	(0.000)	(0.000)	(0.000)
Chief executives, senior officials and legislators	0.048	0.058*	0.060*
	(0.032)	(0.032)	(0.032)
Administrative and commercial managers	-0.015	0.000	-0.009
	(0.029)	(0.029)	(0.029)
Production and specialized services managers	0.034	0.031	0.032
	(0.028)	(0.028)	(0.027)
Hospitality, retail and other services managers	-0.017	-0.021	-0.019
	(0.036)	(0.036)	(0.035)
Science and engineering professionals	-0.004	0.016	0.010
	(0.022)	(0.022)	(0.022)
Health professionals	-0.021	-0.000	0.008
	(0.017)	(0.017)	(0.017)
Teaching professionals	-0.024*	0.014	0.014
	(0.015)	(0.015)	(0.015)
Business and administration professionals	-0.006	0.003	0.004
	(0.022)	(0.022)	(0.022)
Information and communications technology professionals	0.036	0.044	0.043
	(0.037)	(0.037)	(0.036)
Legal, social and cultural professionals	-0.027	-0.000	-0.004
	(0.020)	(0.020)	(0.020)
Science and engineering associate professionals	0.042*	0.039*	0.026
	(0.022)	(0.022)	(0.022)
Health associate professionals	0.022	0.029	0.021
	(0.021)	(0.021)	(0.021)
Legal, social, cultural and related associate professionals	-0.004	-0.005	-0.006
	(0.029)	(0.029)	(0.028)
Information and communications technicians	0.057	0.058	0.037
	(0.059)	(0.058)	(0.057)

General and keyboard clerks	0.016	0.013	0.010
	(0.015)	(0.015)	(0.015)
Customer services clerks	0.048**	0.039*	0.035
	(0.023)	(0.023)	(0.023)
Numerical and material recording clerks	0.039**	0.033*	0.028
	(0.019)	(0.019)	(0.019)
Other clerical support workers	0.016	0.008	0.006
	(0.022)	(0.022)	(0.022)
Personal services workers	0.077***	0.058***	0.048***
	(0.016)	(0.016)	(0.016)
Sales workers	0.052***	0.037**	0.034**
	(0.015)	(0.015)	(0.015)
Personal care workers	0.072***	0.064***	0.058***
	(0.017)	(0.016)	(0.016)
Protective services workers	0.087**	0.069*	0.061
	(0.040)	(0.040)	(0.039)
Market-oriented skilled agricultural workers	0.080***	0.052**	0.045**
	(0.021)	(0.021)	(0.021)
Market-oriented skilled forestry, fishery and hunting workers	0.130***	0.104**	0.110**
	(0.046)	(0.046)	(0.045)
Subsistence farmers, fishers, hunters and gatherers	0.066***	0.038	0.040*
	(0.025)	(0.025)	(0.024)
Building and related trades workers (excluding electricians)	0.071**	0.047	0.043
	(0.032)	(0.032)	(0.031)
Metal, machinery and related trades workers	0.055*	0.035	0.021
	(0.032)	(0.032)	(0.031)
Handicraft and printing workers	0.072***	0.053**	0.043*
	(0.026)	(0.026)	(0.026)
Electrical and electronics trades workers	0.192***	0.177***	0.170***
	(0.049)	(0.049)	(0.048)
Food processing, woodworking, garment and other craft and related trades workers	0.078***	0.058***	0.054***
	(0.016)	(0.016)	(0.016)
Stationary plant and machine operators	0.085***	0.059***	0.048***

	(0.018)	(0.019)	(0.018)
Assemblers	0.108***	0.081**	0.066*
	(0.038)	(0.038)	(0.037)
Drivers and mobile plant operators	0.096***	0.092***	0.082**
	(0.034)	(0.034)	(0.034)
Cleaners and helpers	0.104***	0.073***	0.061***
	(0.017)	(0.017)	(0.017)
Agricultural, forestry and fishery labourers	0.107***	0.078**	0.068**
	(0.032)	(0.032)	(0.031)
Labourers in mining, construction, manufacturing and transport	0.106***	0.080***	0.066***
	(0.021)	(0.021)	(0.020)
Food preparation assistants	0.159***	0.126***	0.114***
	(0.031)	(0.031)	(0.030)
Refuse workers and other elementary workers	0.083**	0.061*	0.043
	(0.036)	(0.036)	(0.036)
Never worked	0.084***	0.056***	0.052***
	(0.015)	(0.015)	(0.015)
No education		0.058***	0.053***
		(0.019)	(0.019)
ISCED 1		0.057***	0.043***
		(0.015)	(0.015)
ISCED 2		0.043***	0.035***
		(0.014)	(0.014)
ISCED 3		0.011	0.007
		(0.013)	(0.012)
ISCED 5		-0.044***	-0.033***
		(0.014)	(0.013)
ISCED 6		-0.181***	-0.159***
		(0.038)	(0.037)
Health childhood			0.156***
			(0.006)
Father: Premature dead			0.067***
			(0.010)
Father: Normal dead			0.061***
			(0.010)

Mother: Premature dead			0.054***
			(0.008)
Mother: Normal dead			0.034***
			(0.008)
Father profession:			
Senior managers and professionals			-0.040***
			(0.011)
Technicians and associate professionals and armed forces			-0.014
			(0.012)
Skilled agricultural and fishery workers			-0.003
			(0.011)
Craftsmen and skilled workers			-0.009
			(0.010)
Elementary occupations and unskilled workers			0.001
			(0.010)
Unknown			-0.010
			(0.011)
_cons	0.121***	0.169***	0.175***
	(0.025)	(0.028)	(0.029)
N	20 614	20 614	20 614
pseudo R^2	13.10 %	13.58 %	17.39 %

The table shows the result of regression (2.1), where OCC refers to the main job. Model 1 includes age in the control variables, Model 2 adds education and Model 3 the childhood circumstances. Our coefficients are reduced when we include more control variables. The job coefficients show a clear gradient with low-arduous occupations, like "Teachers", and high arduous occupations, like "Refuse workers". Standard errors are in parentheses; *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

Table 2.5: Gelbach decomposition - Male

	$\delta_{Education}$	$\delta_{Father's\,occupation}$	$\delta_{Init.Health}$
Chief executives, senior officials and legislators	-0.01528	0.00051	-0.00352
Administrative and commercial managers	-0.01772	-0.00039	-0.00947
Production and specialized services managers	-0.00159	-0.00055	-0.00227
Hospitality, retail and other services managers	-0.00092	0.00108	-0.00897
Science and engineering professionals	-0.02217	-0.00031	0.00394
Health professionals	-0.02601	-0.00048	-0.00076
Teaching professionals	-0.03568	-0.00021	0.00449
Business and administration professionals	-0.01460	-0.00078	-0.00569
Information and communications technology professionals	-0.01990	-0.00157	-0.01560
Legal, social and cultural professionals	-0.02284	-0.00044	0.01058
Science and engineering associate professionals	0.00021	0.00023	0.00357
Health associate professionals	-0.00555	-0.00067	0.01725
Legal, social, cultural and related associate professionals	-0.00182	-0.00070	0.00348
Information and communications technicians	0.00300	0.00095	-0.01005
General and keyboard clerks	0.00059	0.00083	0.00013
Customer services clerks	0.00438	0.00103	0.00378
Numerical and material recording clerks	0.00654	0.00031	-0.00047
Other clerical support workers	0.00869	0.00195	0.00837
Personal services workers	0.01248	0.00204	0.00176
Sales workers	0.01215	-0.00003	0.00575
Personal care workers	0.00405	-0.00123	0.02948
Protective services workers	0.00709	0.00124	0.00798
Market-oriented skilled agricultural workers	0.01682	-0.00031	0.00841
Market-oriented skilled forestry, fishery and hunting workers	0.01715	0.00092	0.01556
Subsistence farmers, fishers, hunters and gatherers	0.02165	-0.00034	-0.00011
Building and related trades workers (excluding electricians)	0.01873	0.00289	0.00929
Metal, machinery and related trades workers	0.01585	0.00239	0.00941
Handicraft and printing workers	0.01396	0.00357	0.01627
Electrical and electronics trades workers	0.01207	0.00254	0.01088

Food processing, woodworking, garment and other craft and related trades workers	0.01545	0.00249	0.00855
Stationary plant and machine operators	0.01693	0.00271	0.01151
Assemblers	0.01217	0.00287	0.01675
Drivers and mobile plant operators	0.02137	0.00238	0.00557
Cleaners and helpers	0.01296	0.00204	0.00956
Agricultural, forestry and fishery labourers	0.01936	0.00252	0.00703
Labourers in mining, construction, manufacturing and transport	0.02057	0.00203	0.01208
Food preparation assistants	0.01158	-0.00228	0.04611
Refuse workers and other elementary workers	0.01879	0.00169	0.02252
Never worked	0.01587	0.00137	0.01140

The table shows the Gelbach (2016) decomposition. The $\delta_{Education}$ is the part due to education of the change between the occupation coefficients of column 1 and 3 in Table 2.3.

Table 2.6: Gelbach decomposition - Female

	$\delta_{Education}$	$\delta_{Father's\,occupation}$	$\delta_{Init.Health}$
Chief executives, senior officials and legislators	-0.00717	- 0.00855	0.00426
Administrative and commercial managers	-0.01181	-0.00255	0.00874
Production and specialized services managers	0.00268	-0.00492	0.00439
Hospitality, retail and other services managers	0.00348	- 0.00055	-0.00102
Science and engineering professionals	-0.01535	-0.00524	0.00693
Health professionals	-0.01634	-0.00284	-0.01017
Teaching professionals	-0.02983	-0.00381	-0.00501
Business and administration professionals	-0.00728	-0.00212	-0.00056
Information and communications technology professionals	-0.00619	-0.00212	0.00059
Legal, social and cultural professionals	-0.02105	-0.00467	0.00208
Science and engineering associate professionals	0.00212	-0.00111	0.01409
Health associate professionals	-0.00585	-0.00129	0.00723
Legal, social, cultural and related associate professionals	0.00110	-0.00109	0.00128
Information and communications technicians	-0.00073	0.00285	0.01726
General and keyboard clerks	0.00183	0.00021	0.00305
Customer services clerks	0.00756	-0.00001	0.00580
Numerical and material recording clerks	0.00466	0.00024	0.00573
Other clerical support workers	0.00636	0.00023	0.00294
Personal services workers	0.01446	0.00254	0.01166
Sales workers	0.01133	0.00178	0.00498
Personal care workers	0.00593	0.00089	0.00750
Protective services workers	0.01511	0.00354	0.00697
Market-oriented skilled agricultural workers	0.02278	0.00312	0.00906
Market-oriented skilled forestry, fishery and hunting workers	0.02023	0.00153	-0.00164
Subsistence farmers, fishers, hunters and gatherers	0.02218	0.00391	-0.00041
Building and related trades workers (excluding electricians)	0.01868	0.00245	0.00663
Metal, machinery and related trades workers	0.01535	0.00156	0.01719
Handicraft and printing workers	0.01521	0.00193	0.01188
Electrical and electronics trades workers	0.01169	-0.00270	0.01271

Food processing, woodworking, garment and other craft and related trades workers	0.01546	0.00192	0.00659
Stationary plant and machine operators	0.02092	0.00298	0.01304
Assemblers	0.02155	0.00309	0.01784
Drivers and mobile plant operators	0.00349	0.00273	0.00802
Cleaners and helpers	0.02416	0.00353	0.01518
Agricultural, forestry and fishery labourers	0.02368	0.00235	0.01315
Labourers in mining, construction, manufacturing and transport	0.02090	0.00280	0.01649
Food preparation assistants	0.02581	0.00208	0.01654
Refuse workers and other elementary workers	0.01733	0.00117	0.02106
Never worked	0.02219	0.00123	0.00796

The table shows the Gelbach (2016) decomposition. The $\delta_{Education}$ is the part due to education of the change between the occupation coefficients of column 1 and 3 in Table 2.4.

Table 2.7: Spearman correlation across regressions inside country groups

	Male			Female		
	High	Middle	Low	High	Middle	Low
Main job vs. Time in each job	93,99%	92,11%	84,33%	91,96%	95,93 %	86,61 %
Main job vs. First job	70,53%	73,50%	64,92%	80,87%	86,76%	78,40%
Main job vs. Last job	90,97%	90,95%	82,84%	90,04%	90,36%	77,53%
Baseline vs. + Education	96,44%	96,51%	94,57%	97,11%	96,42%	92,63%
Baseline vs. + Education and health endowment	95,16%	93,85%	94,35%	95,50%	91,56%	87,79%

The table shows the Spearman correlation across regressions inside country groups. Countries are divided into three groups based on their GDP per capita. The different regressions are those used previously in the paper. First, we change the occupation variable and, then, we add more controls.

Table 2.8: Career length differentiation for male

	Column 1	Column 2	Column 3
Food preparation assistants	-38.25	-41.52	-45.40
Assemblers	-15.38	-16.69	-18.25
Market-oriented skilled forestry, fishery and hunting workers	-12.77	-13.86	-15.16
Labourers in mining, construction, manufacturing and transport	-11.83	-12.85	-14.05
Metal, machinery and related trades workers	-10.82	-11.75	-12.85
Agricultural, forestry and fishery labourers	-10.33	-11.22	-12.27
Drivers and mobile plant operators	-10.19	-11.07	-12.10
Building and related trades workers (excluding electricians)	-10.10	-10.97	-11.99
Refuse workers and other elementary workers	-9.88	-10.72	-11.73
Subsistence farmers, fishers, hunters and gatherers	-9.06	-9.84	-10.76
Handicraft and printing workers	-8.93	-9.70	-10.60
Personal care workers	-8.84	-9.60	-10.49
Electrical and electronics trades workers	-8.37	-9.09	-9.94
Personal services workers	-7.21	-7.82	-8.56
Health associate professionals	-7.06	-7.66	-8.38
Food processing, woodworking, garment and other craft and related trades workers	-6.41	-6.96	-7.61
Stationary plant and machine operators	-6.22	-6.75	-7.38
Science and engineering associate professionals	-5.51	-5.98	-6.54
Market-oriented skilled agricultural workers	-4.70	-5.10	-5.78
Other clerical support workers	-4.09	-4.44	-4.85
Production and specialized services managers	-3.68	-4.00	-4.37
Business and administration professionals	-3.53	-3.83	-4.19
Protective services workers	-2.24	-2.43	-2.65
Cleaners and helpers	-1.08	-1.17	-1.28
Legal, social, cultural and related associate professionals	-0.65	-0.70	-0.77
Hospitality, retail and other services managers	-0.30	-0.33	-0.36
Sales workers	1.26	1.37	1.50
Customer services clerks	1.39	1.51	1.65

Science and engineering professionals	1.73	1.88	2.05
General and keyboard clerks	1.81	1.96	2.15
Information and communications technology professionals	2.56	2.78	3.04
Numerical and material recording clerks	2.76	2.99	3.27
Administrative and commercial managers	3.66	3.97	4.34
Legal, social and cultural professionals	3.71	4.03	4.41
Teaching professionals	3.91	4.24	4.64
Chief executives, senior officials and legislators	5.55	6.03	6.59
Health professionals	5.61	6.09	6.66
Information and communications technicians	5.68	6.16	6.74

The table shows the difference of career lengths by profession for male. They are calculated based on the division of the main occupation coefficient by the age one. Column 1 is the calculus when we take the upper bound of the 95 % confidence interval of the age coefficient, Column 2 is the coefficient and Column 3 is the lower bound of the 95 % confidence interval.

Table 2.9: Career length differentiation for female

	Column 1	Column 2	Column 3
Electrical and electronics trades workers	-21.62	-22.99	-24.55
Food preparation assistants	-17.90	-19.04	-20.34
Market-oriented skilled forestry, fishery and hunting workers	-14.67	-15.60	-16.66
Assemblers	-12.24	-13.02	-13.90
Agricultural, forestry and fishery labourers	-12.10	-12.87	-13.74
Labourers in mining, construction, manufacturing and transport	-11.97	-12.73	-13.60
Cleaners and helpers	-11.68	-12.43	-13.27
Drivers and mobile plant operators	-10.86	-11.55	-12.33
Protective services workers	-9.82	-10.44	-11.15
Stationary plant and machine operators	-9.60	-10.21	-10.90
Refuse workers and other elementary workers	-9.31	-9.91	-10.58
Market-oriented skilled agricultural workers	-9.02	-9.59	-10.25
Food processing, woodworking, garment and other craft and related trades workers	-8.83	-9.39	-10.03
Personal services workers	-8.66	-9.21	-9.83
Handicraft and printing workers	-8.13	-8.64	-9.23
Personal care workers	-8.11	-8.63	-9.21
Building and related trades workers (excluding electricians)	-7.96	-8.47	-9.04
Subsistence farmers, fishers, hunters and gatherers	-7.40	-7.87	-8.40
Information and communications technicians	-6.39	-6.79	-7.25
Metal, machinery and related trades workers	-6.17	-6.56	-7.01
Sales workers	-5.87	-6.24	-6.67
Customer services clerks	-5.46	-5.81	-6.10
Chief executives, senior officials and legislators	-5.44	-5.79	-6.18
Science and engineering associate professionals	-4.69	-4.99	-5.33
Numerical and material recording clerks	-4.38	-4.66	-4.98
Information and communications technology professionals	-4.03	-4.28	-4.57
Production and specialized services managers	-3.83	-4.07	-4.35

Health associate professionals	-2.43	-2.59	-2.76
Other clerical support workers	-1.80	-1.91	-2.04
General and keyboard clerks	-1.76	-1.87	-2.00
Science and engineering professionals	0.40	0.42	0.45
Legal, social, cultural and related associate professionals	0.49	0.52	0.55
Business and administration professionals	0.71	0.75	0.80
Administrative and commercial managers	1.70	1.81	1.93
Hospitality, retail and other services managers	1.88	2.00	2.13
Health professionals	2.41	2.56	2.73
Teaching professionals	2.74	2.92	3.12
Legal, social and cultural professionals	3.10	3.30	3.53

The table shows the difference of career lengths by profession for female. They are calculated based on the division of the main occupation coefficient by the age one. Column 1 is the calculus when we take the upper bound of the 95 % confidence interval of the age coefficient, Column 2 is the coefficient and Column 3 is the lower bound of the 95 % confidence interval.

Table 2.10: Variance decomposition - Male

	Part of the variance			
	All	High	Middle	Low
Education	5.56%	8.18%	2.81%	3.66%
	(1.056)	(2.275)	(1.498)	(1.341)
Occupations	7.07%	14.76%	6.57%	6.10%
	(1.717)	(4.083)	(4.523)	(3.871)
Age	15.94%	13.76%	19.37%	16.31%
	(1.490)	(2.605)	(2.846)	(2.288)
Country	35.18%	21.67%	30.95%	44.97%
	(1.874)	(3.280)	(3.382)	(4.039)
Childhood conditions	35.80%	40.81%	39.88%	28.32%
	(1.900)	(4.359)	(3.871)	(3.312)
Father's occupation	0.45%	0.83%	0.42%	0.65%
	(0.575)	(1.136)	(1.037)	(1.294)
Difference Occ High-Middle:	8.05**	(3.811)		
Difference Occ High-Low:	8.45**	(3.790)		
Difference Occ Middle-Low:	0.40	(3.029)		

The table shows the part of the variance explained by the different variables. The most important variables are childhood conditions and country.

Table 2.11: Variance decomposition - Female

	Part of the variance			
	All	High	Middle	Low
Education	6.63%	9.16%	3.11%	5.48 %
	(1.081)	(1.887)	(1.394)	(1.264)
Occupations	4.06%	10.05%	5.10%	3.02%
	(1.264)	(2.818)	(2.464)	(2.766)
Age	18.82%	17.28%	23.37%	18.82%
	(1.384)	(2.369)	(2.659)	(1.766)
Country	32.35%	25.70%	19.58%	38.36%
	(1.624)	(2.655)	(2.161)	(3.057)
Childhood conditions	36.79%	37.33%	47.65%	31.54%
	(1.793)	(3.280)	(2.882)	(3.063)
Father's occupation	1.36%	0.49%	1.18%	2.78%
	(0.590)	(0.812)	(0.886)	(1.266)
Difference Occ High-Middle:	4.95**	(2.266)		
Difference Occ High-Low:	7.03***	(2.289)		
Difference Occ Middle-Low:	2.08	(2.091)		

The table shows the part of the variance explained by the different variables. The most important variables are childhood conditions and country.

Table 2.12: Robustness test - Male

	(1)	(2)	(3)
	All obs	< 70	ACP
Age	0.006***	0.007***	0.010***
	(0.000)	(0.000)	(0.000)
Chief executives, senior officials and legislators	-0.031	-0.034	-0.020
	(0.027)	(0.036)	(0.032)
Administrative and commercial managers	-0.005	-0.000	0.004
	(0.030)	(0.041)	(0.036)
Production and specialized services managers	0.032	0.048	0.048
	(0.027)	(0.039)	(0.032)
Hospitality, retail and other services managers	0.011	-0.004	-0.031
	(0.038)	(0.050)	(0.046)
Science and engineering professionals	0.003	0.005	-0.020
	(0.021)	(0.029)	(0.025)
Health professionals	-0.022	-0.044	0.023
	(0.030)	(0.039)	(0.035)
Teaching professionals	-0.003	-0.002	0.009
	(0.022)	(0.031)	(0.027)
Business and administration professionals	0.052*	0.037	-0.012
	(0.031)	(0.043)	(0.037)
Information and communications technology professionals	-0.013	-0.008	-0.010
	(0.036)	(0.044)	(0.042)
Legal, social and cultural professionals	-0.020	-0.014	0.011
	(0.028)	(0.038)	(0.034)
Science and engineering associate professionals	0.045**	0.050*	0.022
	(0.020)	(0.027)	(0.024)
Health associate professionals	0.051	0.018	0.037
	(0.037)	(0.048)	(0.044)
Legal, social, cultural and related associate professionals	0.005	0.026	0.014
	(0.037)	(0.046)	(0.044)
Information and communications technicians	-0.017	-0.036	-0.017
	(0.042)	0.052	(0.050)

General and keyboard clerks	-0.017	-0.028	-0.027
	(0.026)	(0.034)	(0.031)
Customer services clerks	-0.021	0.026	0.026
	(0.036)	(0.046)	(0.043)
Numerical and material recording clerks	-0.031	-0.013	0.027
	(0.029)	(0.039)	(0.035)
Other clerical support workers	0.017	0.047	-0.047
	(0.033)	(0.044)	(0.039)
Personal services workers	0.047*	0.074**	0.018
	(0.026)	(0.033)	(0.031)
Sales workers	-0.029	-0.035	-0.034
	(0.025)	(0.033)	(0.029)
Personal care workers	0.046	0.049	0.028
	(0.055)	(0.065)	(0.065)
Protective services workers	0.003	0.028	-0.025
	(0.027)	(0.035)	(0.032)
Market-oriented skilled agricultural workers	0.017	0.036	0.049
	(0.025)	(0.037)	(0.030)
Market-oriented skilled forestry, fishery and hunting workers	0.079**	0.097**	0.078*
	(0.037)	(0.049)	(0.044)
Subsistence farmers, fishers, hunters and gatherers	0.059**	0.062	0.077**
	(0.029)	(0.039)	(0.035)
Building and related trades workers (excluding electricians)	0.058***	0.067***	0.065***
	(0.019)	(0.025)	0.023
Metal, machinery and related trades workers	0.068***	0.090***	0.022
	(0.019)	(0.025)	(0.022)
Handicraft and printing workers	0.045	0.043	0.062*
	(0.030)	(0.040)	(0.036)
Electrical and electronics trades workers	0.048**	0.071**	0.079***
	(0.023)	(0.030)	(0.027)
Food processing, woodworking, garment and other craft and related trades workers	0.030	0.041	0.028
	(0.024)	(0.032)	(0.028)
Stationary plant and machine operators	0.024	0.043	0.054**

	(0.023)	(0.030)	(0.027)
Assemblers	0.104***	0.141***	0.117***
	(0.038)	(0.049)	(0.045)
Drivers and mobile plant operators	0.061***	0.078***	0.042*
	(0.019)	(0.026)	(0.023)
Cleaners and helpers	-0.015	0.030	0.129
	(0.074)	(0.088)	(0.088)
Agricultural, forestry and fishery labourers	0.062	0.088	0.021
	(0.043)	(0.064)	(0.051)
Labourers in mining, construction, manufacturing and transport	0.070***	0.085***	0.078***
	(0.022)	(0.029)	(0.027)
Food preparation assistants	0.282*	0.401*	0.256
	(0.148)	(0.238)	(0.176)
Refuse workers and other elementary workers	0.044	0.067	0.060
	(0.038)	(0.048)	(0.045)
Never worked	0.020	0.023	0.091***
	(0.029)	(0.040)	0.035
ISCED 0	0.022	0.013	0.118***
	(0.023)	(0.034)	(0.028)
ISCED 1	0.026	0.029	0.077***
	(0.018)	(0.025)	(0.021)
ISCED 2	0.029*	0.018	0.057***
	(0.017)	(0.022)	(0.020)
ISCED 3	0.009	-0.003	0.020
	(0.015)	(0.019)	(0.018)
ISCED 5	-0.046***	-0.060***	-0.011
	(0.016)	(0.021)	(0.019)
ISCED 6	-0.113***	-0.160***	-0.088**
	(0.034)	(0.047)	(0.040)
Health childhood	0.162***	0.191***	0.115***
	(0.007)	(0.009)	(0.008)
Father: Premature dead	0.088***	0.077***	0.046***
	(0.012)	(0.014)	(0.015)
Father: Normal dead	0.072***	0.066***	0.019
	(0.012)	(0.014)	(0.015)

Mother: Premature dead	0.025***	0.023**	0.016
	(0.010)	(0.011)	(0.011)
Mother: Normal dead	0.017*	0.008	0.006
	(0.010)	(0.012)	(0.012)
Father profession:			
Senior managers and professionals	-0.003	0.008	-0.025
	(0.013)	(0.018)	(0.016)
Technicians and associate professionals and armed forces	-0.028*	-0.011	-0.019
	(0.015)	(0.020)	(0.018)
Skilled agricultural and fishery workers	-0.003	-0.003	-0.012
	(0.013)	(0.018)	(0.015)
Craftsmen and skilled workers	0.006	0.010	-0.028**
	(0.012)	(0.016)	(0.014)
Elementary occupations and unskilled workers	0.006	0.016	0.003
	(0.013)	(0.017)	(0.015)
Unknown	-0.002	0.006	-0.046***
	(0.014)	(0.018)	(0.016)
_cons	0.150***	0.077	-0.288***
	(0.037)	(0.064)	(0.044)
N	15 221	9 807	15 221
R^2	15.77 %	16.44 %	11.71 %

The table shows the robustness of our results. The first column refers to our previous result, the second to an estimation based on a sample with only the observations younger than 70 and the third column uses another indicator of health. This indicator is obtained from a PCA on several questions related to health. Standard errors are in parentheses; *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

Table 2.13: Variance decomposition (Male) - Robustness

	Part of the variance		
	All	< 70	ACP
Education	5.56%	5.83%	5.23%
	(1.056)	(1.153)	(0.912)
Occupations	7.07%	9.20%	6.37%
	(1.717)	(2.461)	(2.137)
Age	15.94%	6.76%	33.70%
	(1.490)	(1.339)	(2.476)
Country	35.18%	40.05%	34.96%
	(1.874)	(2.379)	(2.193)
Childhood conditions	35.80%	37.89%	18.85%
	(1.900)	(2.375)	(2.122)
Father's occupation	0.45%	0.27%	0.89%
	(0.575)	(0.730)	(0.709)

The table shows the robustness of our results. The first column refers to our previous result, the second to an estimation based on a sample with only the observations younger than 70 and the third column uses another indicator of health. This indicator is obtained from a PCA on several questions related to health.

Table 2.14: Robustness test - Female

	(1)	(2)	(3)
	All obs	< 70	ACP
Age	0.006***	0.007***	0.011***
	(0.000)	(0.001)	(0.000)
Chief executives, senior officials and legislators	0.060*	0.077*	-0.031
	(0.032)	(0.042)	(0.039)
Administrative and commercial managers	-0.009	-0.008	-0.041
	(0.029)	(0.036)	(0.035)
Production and specialized services managers	0.032	0.039	-0.013
	(0.027)	(0.038)	(0.034)
Hospitality, retail and other services managers	-0.019	-0.045	0.020
	(0.035)	(0.047)	(0.043)
Science and engineering professionals	0.010	-0.008	0.006
	(0.022)	(0.031)	(0.027)
Health professionals	0.008	0.007	0.029
	(0.017)	(0.022)	(0.021)
Teaching professionals	0.014	0.009	0.024
	(0.015)	(0.020)	(0.019)
Business and administration professionals	0.004	-0.014	-0.003
	(0.022)	(0.029)	(0.027)
Information and communications technology professionals	0.043	0.064	-0.010
	(0.036)	(0.047)	(0.045)
Legal, social and cultural professionals	-0.004	0.006	0.000
	(0.020)	(0.026)	(0.035)
Science and engineering associate professionals	0.026	0.050*	0.020
	(0.022)	(0.029)	(0.027)
Health associate professionals	0.021	0.014	-0.006
	(0.021)	(0.027)	(0.026)
Legal, social, cultural and related associate professionals	-0.006	-0.011	0.001
	(0.028)	(0.036)	(0.024)
Information and communications technicians	0.037	-0.009	-0.062
	(0.057)	(0.075)	(0.071)

General and keyboard clerks	0.010	0.002	-0.013
	(0.015)	(0.020)	(0.018)
Customer services clerks	0.035	0.055*	0.015
	(0.023)	(0.031)	(0.028)
Numerical and material recording clerks	0.028	0.029	0.017
	(0.019)	(0.025)	(0.023)
Other clerical support workers	0.006	-0.003	0.009
	(0.022)	(0.028)	(0.027)
Personal services workers	0.048***	0.050**	0.045**
	(0.016)	(0.021)	(0.020)
Sales workers	0.034**	0.022	0.030
	(0.015)	(0.020)	0.019
Personal care workers	0.058***	0.057***	0.041**
	(0.016)	(0.021)	(0.020)
Protective services workers	0.061	0.062	0.009
	(0.039)	(0.054)	(0.048)
Market-oriented skilled agricultural workers	0.045**	0.047	0.060**
	(0.021)	(0.031)	(0.025)
Market-oriented skilled forestry, fishery and hunting workers	0.110**	0.130*	0.075
	(0.045)	(0.069)	(0.056)
Subsistence farmers, fishers, hunters and gatherers	0.040*	0.037	0.128***
	(0.024)	(0.033)	(0.030)
Building and related trades workers (excluding electricians)	0.043	0.042	0.070*
	(0.031)	(0.041)	(0.039)
Metal, machinery and related trades workers	0.021	0.039	0.024
	(0.031)	(0.041)	(0.039)
Handicraft and printing workers	0.043*	0.059*	0.062**
	(0.026)	(0.036)	(0.032)
Electrical and electronics trades workers	0.170***	0.198***	0.159***
	(0.048)	(0.061)	(0.059)
Food processing, woodworking, garment and other craft and related trades workers	0.054***	0.061***	0.062***
	(0.016)	(0.022)	(0.020)
Stationary plant and machine operators	0.048***	0.049**	0.063***

	(0.018)	(0.025)	(0.023)
Assemblers	0.066*	0.048	0.103**
	(0.037)	(0.047)	(0.046)
Drivers and mobile plant operators	0.082**	0.100**	0.085**
	(0.034)	(0.044)	(0.042)
Cleaners and helpers	0.061***	0.073***	0.079***
	(0.017)	(0.022)	(0.021)
Agricultural, forestry and fishery labourers	0.068**	0.121***	0.086**
	(0.031)	(0.049)	(0.039)
Labourers in mining, construction, manufacturing and transport	0.066***	0.063**	0.034
	(0.020)	(0.027)	(0.025)
Food preparation assistants	0.114***	0.139***	0.105***
	(0.030)	(0.042)	(0.038)
Refuse workers and other elementary workers	0.043	0.038	0.076*
	(0.036)	(0.048)	(0.044)
Never worked	0.052***	0.046**	0.062***
	(0.015)	(0.021)	(0.018)
ISCED 0	0.053***	0.084***	0.133***
	(0.019)	(0.030)	(0.023)
ISCED 1	0.043***	0.092***	0.084***
	(0.015)	(0.021)	(0.018)
ISCED 2	0.035***	0.075***	0.071***
	(0.014)	(0.019)	(0.017)
ISCED 3	0.007	0.033**	0.030*
	(0.012)	(0.017)	(0.016)
ISCED 5	-0.033***	-0.019	-0.011
	(0.013)	(0.018)	(0.016)
ISCED 6	-0.159***	-0.217***	-0.027
	(0.037)	(0.050)	(0.046)
Health childhood	0.156***	0.186***	0.121***
	(0.006)	(0.008)	(0.007)
Father: Premature dead	0.067***	0.057***	0.031***
	(0.010)	(0.011)	(0.012)
Father: Normal dead	0.061***	0.045***	0.008
	(0.010)	(0.011)	(0.012)

Mother: Premature dead	0.054***	0.045***	0.028***
	(0.008)	(0.009)	(0.010)
Mother: Normal dead	0.034***	0.020**	-0.004
	(0.008)	(0.010)	(0.010)
Father profession:			
Senior managers and professionals	-0.040***	-0.041***	-0.041***
	(0.011)	(0.015)	(0.014)
Technicians and associate professionals and armed forces	-0.014	-0.019	-0.000
	(0.012)	(0.017)	(0.015)
Skilled agricultural and fishery workers	-0.003	-0.009	-0.030**
	(0.011)	(0.015)	(0.013)
Craftsmen and skilled workers	-0.009	-0.019	-0.023*
	(0.010)	(0.013)	(0.012)
Elementary occupations and unskilled workers	0.001	-0.002	-0.010
	(0.010)	(0.014)	(0.013)
Unknown	-0.010	-0.010	-0.013
	(0.011)	(0.015)	(0.014)
_cons	0.175***	0.060	-0.374***
	(0.029)	(0.049)	(0.036)
N	20 614	13 374	20 614
pseudo R^2	17.39 %	17.37 %	14.28 %

The table shows the robustness of our results. The first column refers to our previous result, the second to an estimation based on a sample with only the observations younger than 70 and the third column uses another indicator of health. This indicator is obtained from a PCA on several questions related to health. Standard errors are in parentheses; *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

Table 2.15: Variance decomposition (Female) - Robustness

	Part of the variance		
	All	< 70	ACP
Education	5.48 %	7.62%	6.98 %
	(1.264)	(1.171)	(1.158)
Occupations	3.02%	4.79 %	5.03%
	(2.766)	(1.418)	(1.364)
Age	18.82%	7.95 %	42.70%
	(1.766)	(1.407)	(2.171)
Country	38.36%	40.38 %	27.50%
	(3.057)	(1.909)	(1.438)
Childhood conditions	31.54%	38.06 %	17.54 %
	(3.063)	(1.952)	(1.599)
Father's occupation	2.78%	1.20 %	0.25%
	(1.266)	(0.674)	(0.417)

The table shows the robustness of our results. The first column refers to our previous result, the second to an estimation based on a sample with only the observations younger than 70 and the third column uses another indicator of health. This indicator is obtained from a PCA on several questions related to health.

2.8 Appendix

Appendix A: Full Gelbach decomposition: An illustration for two contrasted occupations

We illustrate here the decomposition of the Gelbach-estimated contribution of education $\delta^{Education}$ to lowering the magnitude of the correlation between occupation and the risk of being in poor health. We consider two a priori contrasted main occupations: "Food preparation assistants" and "Chief Executives, senior officials and legislators", bearing in mind the reference profession is "Business and associate professionals".

Table 2.5 (results for male respondents) shows that $\delta^{Education}$ is .01158 for "Food preparation assistants" and -.01528 for "Chief Executives, senior officials and legislators". As our education variable consists of a series of ISCED dummies, for each considered occupation, $\delta^{Education} = \sum_l \delta^{ISCED_l}, l = 0, 1, 2, 3, 5, 6\ (ref. = 4)$. And following (2.6) each δ^{ISCED_l} is the cross-product of the γ^{ISCED_l}'s (reported in Tables 2.3 and 2.4) by ISCED specific ρ's. More precisely:

- "Food preparation assistants"

$$\underbrace{.01158}_{\delta^{Education}} = \underbrace{.23764 \times .022}_{\rho^{ISCED\,0} \times \gamma^{ISCED\,0}} + \underbrace{-.01932 \times .026}_{\rho^{ISCED\,1} \times \gamma^{ISCED\,1}} + \underbrace{-.07331 \times .029}_{\rho^{ISCED\,2} \times \gamma^{ISCED\,2}} + \underbrace{.12980 \times .009}_{\rho^{ISCED\,3} \times \gamma^{ISCED\,3}} + \underbrace{-.16606 \times -.046}_{\rho^{ISCED\,5} \times \gamma^{ISCED\,5}} + \underbrace{-0.00234 \times -.113}_{\rho^{ISCED\,6} \times \gamma^{ISCED\,6}}$$

  Note the role of $\rho^{ISCED\,3} = .12980$ (i.e. a higher propensity to be $ISCED\,3$) and $\rho^{ISCED\,5} = -.16606$ (i.e. a lower propensity to be $ISCED\,5$) in contributing to $\delta > 0$.

- "Chief Executives, senior officials and legislators"

$$\underbrace{-.01528}_{\delta^{Education}} = \underbrace{.00008 \times .022}_{\rho^{ISCED\,0} \times \gamma^{ISCED\,0}} + \underbrace{-.00644 \times .026}_{\rho^{ISCED\,1} \times \gamma^{ISCED\,1}} + \underbrace{-.05863 \times .029}_{\rho^{ISCED\,2} \times \gamma^{ISCED\,2}} + \underbrace{-.13735 \times .009}_{\rho^{ISCED\,3} \times \gamma^{ISCED\,3}} + \underbrace{.21522 \times -.046}_{\rho^{ISCED\,5} \times \gamma^{ISCED\,5}} + \underbrace{.02032 \times -.113}_{\rho^{ISCED\,6} \times \gamma^{ISCED\,6}}$$

Chapter 3

The limited power of socioeconomic status to predict lifespan: Implications for pension policy

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Differences in life expectancy across socioeconomic status are well known and many economists argue that they should be taken into account when designing pension systems. This chapter analyses the relevance of using socioeconomic characteristics to differentiate the retirement age. Using US mortality rates assembled by Chetty et al. (2016), we simulate the lifespan distribution both across and within socioeconomic categories. Then, we analyse these categories' ability to predict the lifespan of individuals. Results suggest that socioeconomic status has a relatively limited predictive power, due to the huge lifespan heterogeneity "within" each of them.

3.1 Introduction

Extensive research by demographers and economists has shown that life expectancy differs across socioeconomic status, with low-educated or low-income people living, on average, shorter lives than their better-endowed and wealthier peers (see e.g. Olshansky et al., 2012; Chetty et al., 2016). This socioeconomic gradient impacts the pension system in several ways. First, it decreases the lifetime progressivity of the pension system. Bommier et al. (2011) have shown that the progressivity of the French pension system is reduced by one quarter to one half when differences of life expectancy are taken into account and Haan et al.

(2019) suggest that the German pension system becomes regressive. Second, the historical core function assigned to pension systems is to insure against the risk of living a long life. If different socioeconomic groups have different survival probabilities and are aware of it, the undifferentiated "price" of the insurance will be above/below its optimal level. Third, retirement is now seen as something more than a period where work is no longer possible (and synonymous of a risk of poverty that needs to be insured). It is also perceived as a "reward" (or the right to retire from the obligation to work to earn a living) after a long career. If some individuals could expect to live less than others; the size of their rewards is different without any clear reason for it. Visions of pensions as "reward" vs. "insurance" *de facto* coexist, but create apparent normative contradictions.[1] A *very* egalitarian social planner would prefer that everyone enjoys the same time in retirement (in length or percentage). However, in such a case, there is no possibility to pool people for insurance against the risk of living a long life. On the other side, the easiest way to provide an insurance is to pool everyone together; but, by doing so, the outcome is not egalitarian. This said, intermediate situations are probably those where the two objectives cohabit. If the strict egalitarian agenda is only partially fulfilled (as this chapter will show is very likely); then, the insurance role of pensions can remain due to the incapacity of the planner to fulfil her egalitarian agenda. In this chapter, we focus on the egalitarian reason for differentiating the retirement age in order to try to equalise the time spent in retirement "as-a-reward". As a preamble, we should also say that our egalitarian perspective deviates from the one underpinning most of the existing empirical pension literature. Its (usual) policy recommendation has been to differentiate retirement age of groups of individuals defined by their socioeconomic status (including their occupations) (see e.g. Ayuso et al., 2017). The theoretical literature has reached similar conclusions (see e.g. Leroux et al., 2015, for a survey). However, those policies do not take into account the heterogeneity of lifespan within socioeconomic status. To the best of our knowledge, existing empirical works by economists on retirement age differentiation only focus on the problem of compensating individuals for life expectancy differences. This chapter stresses the importance of also considering lifespan heterogeneity.

The difference between life expectancy and lifespan is a key point of this chapter. Whereas life expectancy is the number of years someone can (at a given age) *expect* to live, her lifespan is the number of years she *actually* lives. Life expectancy is an indicator that "hides" the (potentially important) distribution of lifespan inside each socioeconomic status. If policies are based on life expectancy differences, individuals living less/more than their life expectancy will end up being treated with the wrong policy. Although the importance of this problem

[1]See Valente Sa (2022) for a (philosophical) analysis of justice in retirement pensions.

has been addressed theoretically; it has not received much attention in the empirical literature. Pestieau and Racionero (2016) build a model with short-lived and long-lived individuals working either in a harsh or a safe occupation. Realistically, they assume that short-lived workers are over-represented in harsh occupations. Lifespan (i.e. being short- or long-lived) is private information, but occupation is observable and can be used as a "tag" for lifespan by policy-makers. They show that the social planner established a common lower retirement age for short-lived individuals (whatever their occupations) in the first best solution.[2] Then, they discuss the optimal second-best and compare two options: a common social security policy across occupations and tagging (i.e. differentiated retirement age by occupation). They conclude that there is a case for differentiating the retirement age by occupation. However, such a result is not as straightforward as one would assume. Notably, because "the short-lived workers in safe occupations are harmed from being mixed up with a large proportion of long-lived workers, (...) and the long-lived workers in harsh occupations [undeservedly] gain from being pooled with a large number of short-lived workers" (Pestieau and Racionero, 2016, p. 200). There is an immediate parallel with individuals divided by socioeconomic status, characterized by a significant lifespan heterogeneity within socioeconomic status. In both cases, information is not known (or used) by the policy-makers. Although, it is not clearly mentioned in the literature, differentiating the retirement age according to the socioeconomic gradient in life expectancy follows the "tagging" principle introduced by Akerlof (1978). According to him, social policy should be based on "tags" to reach the needy. However, tagging is imperfect and individuals can end up misclassified. Short-lived individuals could be tagged as long-lived because they are mixed in a group with long-lived individuals. This misclassification arises because the decision-maker uses observable characteristics (e.g. job) to infer unobservable ones (e.g. lifespan). Using terms introduced by Phelps (1972), the decision-maker discriminates "statistically" against short-lived people working in soft occupations.

Drawing from this literature, this chapter investigates empirically the importance for pension policy of lifespan heterogeneity within socioeconomic status. To the best of our knowledge, this has never been done before. We proceed in four steps.

- First, we simulate the lifespan distributions both within and across socioeconomic status for the United States, using mortality rate data assembled by Chetty et al. (2016).

[2]The first best solution requires the social planner to know who is short/long-lived. The social planner is able to equalise the utility of the short-lived and the long-lived in the first best solution.

- Second, we call upon standard practice in normative pension economics and assume that a longer life is always better than a shorter one. The social planner decides on the retirement age and pursues an "egalitarian" objective that consists of equalising the share of lifespan spent in retirement.[3] Under perfect information (i.e. first best), the social planner would choose a different retirement age for each individual based on his lifespan ("individualized retirement age"). However, this is not realistic because it requires knowing, in advance, the lifespan of each individual. As a consequence, like in Pestieau and Racionero (2016), in a second-best world, the social planner can only implement either a uniform retirement age or different retirement ages based on (socioeconomic) tags. As a result, there will be gaps between fully individualized retirement ages and retirement ages chosen by the social planner. The sum of those gaps represents the overall propensity of lifespan to remain unaccounted for under a second-best retirement policy.

- Third, we develop a "gap index" to quantify this propensity. We use it to estimate the gains that could be achieved by moving away from a unique retirement age policy. A key finding of the chapter is that differentiating the retirement age by gender and income percentiles (thus, 200 different retirement ages) would only reduce the gap index by 5%. The relatively small magnitude of this gain is primarily due to the important lifespan dispersion within each socioeconomic status.

- Fourth, we show that our key findings are robust to several specifications of the index reflecting the priorities of the social planner (e.g. her aversion to larger gaps).

Tagging is currently not widely used in pension policy. This is also the case for many other social policies or for taxation; a situation which, to some extent, contrasts with what economic theory recommends (Weinzierl, 2012). However, the current population ageing could make tagging a more common policy tool. Governments struggle to make their pension reforms (often, a higher retirement age) socially acceptable. One common criticism is that the raise of the retirement age should be more "tailored" to each individual's profile and circumstances. For example, Vermeer et al. (2016) show that the population wants the retirement age to be lower for those who have done hazardous jobs. It is therefore important to better assess the pros and cons of tagging in retirement policy.

This chapter considers three possible tags: gender, income and state of residence. That choice is partially driven by data availability. The use of any particular tag raises many

[3] We will say more about the foundations of this objective and its link to traditional pension policy in Section 3.3.

feasibility questions. A traditional one is the risk of moral hazard. Ideally, the social planner should be able to use a tag that the individual could not change. Such, that an individual cannot try to modify her category to switch from one to another in order to benefit from another policy. For example, if a subset L has a lower retirement age, it should not be possible for an individual of subset H to modify her tag to be identified as a member of subset L. Gender is naturally not prone to moral hazard. However, tagging by income percentile or state of residence could be more problematic. Our answer to this problem is the following. Tagging by income is less prone to moral hazard if the policy uses a relative indicator (e.g. percentiles). It is easier to place oneself below/above a particular income threshold than in a particular place in the income distribution (e.g. at the 80$^{\text{th}}$ percentile). Moreover, it would make more sense to tag by lifetime income percentile, which makes the issue even less problematic. We come back to this point in Section 3.5.2. The state of residence is also naturally prone to moral hazard. However, in the particular context of the US and of the Chetty et al. (2016) data we use here, it does not appear to be a powerful tag. Therefore, we presented it more as an example in a first best framework. Another important feasibility aspect is the legality of tagging. Retirement ages were differentiated by sex, which was then made illegal.[4] From a purely economic point of view, it is not clear why states of residence are allowed to differentiate the retirement age based on occupation,[5] but not based on gender. In this chapter, we leave aside those discussions and focus on the intrinsic *relevance* of tagging.

A final remark is that our chapter only deals with retirement age differentiation. Other parameters of retirement policy could be used by an egalitarian social planner. One could imagine a pension policy where the retirement age is uniform and the replacement rate is reduced when lifespan rises.[6] The respective merits of these two policies could be compared and form a fully-fledged research agenda. The point is that both approaches fundamentally depend on the planner knowing the distribution of lifespan. If, as seems inevitable, the social planner can only use proxies (i.e. categories correlated to lifespan), then both policies will be less effective at achieving his objective. At the end, this is fundamentally due to the lack of predictive power of the tags. The magnitude of this problem could be studied by simulating different policy scenarios (e.g. retirement age differentiation, replacement rate

[4]The European Court of Justice bans any form of difference of treatment between women and men as to the legal age of retirement.

[5]They are a lot of special schemes for different professions (e.g. bullfighters in Spain). See Zaidi and Whitehouse (2009).

[6]The formal equivalence between retirement age and replacement rate differentiation is developed in Section 3.3.

differentiation). However, the results would converge. We have chosen to base our chapter on the retirement age because the numeric examination of the retirement age differentiation is more tractable and palatable. A "retirement age gap index" is easier to apprehend (and manipulate) than the corresponding "replacement rate gap index".

This chapter proceeds as follows. Section 3.2 constructs and presents our "gap index" aimed at measuring the relevance of the socioeconomic tag(s) that could be used by a social planner. Section 3.3 discusses how the equalisation of the share of life spent in retirement relates to the more traditional objective functions of pension decision-makers. We explained our simulations in Section 3.4. Section 3.5 details our results. In Section 3.6, we discuss more in-depth some normative principles underpinning the chapter (ex-ante vs. ex-post approach to lifespan and individual vs. group differentiation) and then, we conclude.

3.2 Gap index

In order to introduce our gap index, let us consider a simplified example. Assume that the social planner's policy is that each individual should spend the same share α of her life working/in retirement. Society consists of n members, living a life that varies in length, who can be tagged into two subsets (H and L) of identical size. Subset H enjoys a high life expectancy with half of its members (so, $\frac{1}{4}\,n$) living 4.5 periods and the other half 3.5. Subset L has a lower life expectancy with half of its members living 2.5 periods and the other half 1.5. The social planner is willing to introduce different retirement ages reflecting the lifespan of the different individuals. However, he can only differentiate by subset (H and L), due to his inability to distinguish the short- vs. long-lived within each group. He will choose retirement ages to minimize the sum of the gaps between the individualized retirement age ($\alpha \times 4.5$; $\alpha \times 3.5$; $\alpha \times 2.5$ and $\alpha \times 1.5$) and the one he sets for each subset/the entire set. The individualized retirement age is the one that the social planner would set if he had perfect foresight. The social planner will set the retirement age at $\alpha \times 3$ in case of unique retirement age. This will lead to a sum of gaps between the retirement age and the individualized ones equal to $\alpha\, n$. In contrast, he would set the retirement age at $\alpha \times 4$ for subset H and at $\alpha \times 2$ for subset L, generating a total sum of gaps of $0.5\,\alpha\, n$. Our index will measure the percentage of *improvement* (i.e. the decrease of the gaps) between those two policies; so the decrease in the sum of the gaps between the individualized retirement age and the one(s) of the social planner. In this simple example, it is equal to $0.5\,\alpha\, n/\alpha\, n$ suggesting a gain of 50%. This amounts to saying that the mean gap is reduced by half. It is crucial to notice that our index measures the *improvement* between the worst policy (only one retirement age) and the one suggested (e.g. a different one for each subset).

Let's us now generalize to a society constituted of a set of individuals i split into j mutually exclusive subsets defined by a vector of socioeconomic characteristics. Their lifespan (i.e. age at death) is denoted by $m_{i,j}$. The retirement age policy is represented by the function $\delta\left(m_{i,j}\right)$. Different specifications could be considered. We will mainly use a proportional retirement age (i.e. $\delta\left(m_{i,j}\right) = \alpha\, m_{i,j}$), but we will also check the robustness of our result with a non-strictly linear specification. Our gap index is formulated as follows:

$$I\left(\mathbf{m}\right) = \frac{\sum_{j=1}^{k}\sum_{i=1}^{n_j}|\delta\left(m_{i,j}\right) - \mu_j\left(\mathbf{m_j}\right)|^{\beta}}{\sum_{j=1}^{k}\sum_{i=1}^{n_j}|\delta\left(m_{i,j}\right) - \mu\left(\mathbf{m}\right)|^{\beta}} \tag{3.1}$$

$$s.t. \quad \mu\left(\mathbf{m}\right) \in \underset{\mu(\mathbf{m})}{\arg\min}\sum_{j=1}^{k}\sum_{i=1}^{n_j}|\delta\left(m_{i,j}\right) - \mu\left(\mathbf{m}\right)|^{\beta} \tag{3.2}$$

$$\mu_j\left(\mathbf{m_j}\right) \in \underset{\mu_j\left(\mathbf{m_j}\right)}{\arg\min}\sum_{i=1}^{n_j}|\delta\left(m_{i,j}\right) - \mu_j\left(\mathbf{m_j}\right)|^{\beta}, \forall j \tag{3.3}$$

The index is the sum, over each individual, of the absolute value of gaps between the individualized retirement age $\delta\left(m_{i,j}\right)$ and the differentiated retirement age $\mu_j\left(\mathbf{m_j}\right)$ to the power β (representing gap aversion), divided by the sum of gaps in case of a unique retirement age $\mu\left(\mathbf{m}\right)$. The individualized retirement age $\delta\left(m_{i,j}\right)$ is the one set by the social planner with perfect information about the lifespan of each individual (i.e. it is not chosen by the individual). Individuals retire at $\mu\left(\mathbf{m}\right)$ in case of a unique retirement age, and at $\mu_j\left(\mathbf{m_j}\right)$ for those in the subset j when the social planner chooses to differentiate. Constraint (3.2) ensures that the retirement age set by the social planner is the one minimizing the sum of the gaps in the case of unique retirement age. Constraint (3.3) ensures that the differentiated retirement ages are those minimizing the sum of the gaps for each of the different retirement ages.[7]

The parameter β represents the social planner's degree of aversion to an unequal distribution of the gaps his policy entails. These gaps consist of the difference between the perfectly individualized retirement age $\delta\left(m_{i,j}\right)$ and the one he *de facto* imposes (either the differentiated age $\mu_j\left(\mathbf{m_j}\right)$, or the uniform one $\mu\left(\mathbf{m}\right)$). When $\beta = 1$ (no gap aversion), the social planner is indifferent between *i)* imposing to 1 individual a gap of 10 years and *ii)*

[7] In practice, we use Stata_{16} to compute the gaps brought by every possible retirement age and select the most suitable one.

imposing to 10 individuals a gap of 1 year. Higher values of the parameter ($\beta > 1$) mean that the planner cares more about the magnitude of the gaps affecting a limited number of individuals. Our index has also the following properties:

- The index is relative to the default option of a unique retirement age and takes a value inferior/superior to 1 in case of a better/worse policy;
- The index has a value of zero if each individual has his retirement age set optimally, i.e. $\forall j \, \forall i : \delta(m_{i,j}) = \mu_j(\mathbf{m_j})$;
- The index puts more weight on the short-lived if and only if $\beta > 1$. In particular, the higher β is, the more large/extreme gaps matter;
- The index is invariant to the size of the total population;
- The index respects the anonymity principle.

In the particular case where $\delta(m_{i,j}) = \alpha \, m_{i,j}$, our index reduces to the following expression:

$$I(\mathbf{m}) = \frac{\sum_{j=1}^{k} \sum_{i=1}^{n_j} |\alpha \, m_{i,j} - \alpha \, \mu_j(\mathbf{m_j})|^{\beta}}{\sum_{j=1}^{k} \sum_{i=1}^{n_j} |\alpha \, m_{i,j} - \alpha \, \mu(\mathbf{m})|^{\beta}} \tag{3.4}$$

$$s.t. \quad \mu(\mathbf{m}) \in \arg\min_{\mu(\mathbf{m})} \sum_{j=1}^{k} \sum_{i=1}^{n_j} |\alpha \, m_{i,j} - \alpha \, \mu(\mathbf{m})|^{\beta} \tag{3.5}$$

$$\mu_j(\mathbf{m_j}) \in \arg\min_{\mu_j(\mathbf{m_j})} \sum_{i=1}^{n_j} |\alpha \, m_{i,j} - \alpha \, \mu_j(\mathbf{m_j})|^{\beta}, \forall j \tag{3.6}$$

Some additional properties stem from this particular specification. First, the index does not depend on α. Second, the index does not vary with the length of lifespan (multiplicative and additive). Third, it can be shown (see Section 3.8) that the pair $(\alpha \, \mu(\mathbf{m}) ; \alpha \, \mu_j(\mathbf{m_j}))$ corresponds to the median lifespan if β is equal to 1 and to the mean lifespan for a value of β of 2. Above 2, the most appropriate values do not correspond to any usual statistical moment and are numerically identified.

3.3 Gap index and traditional pension policy

Pension economists might be surprised by the main specification of $\delta(m_{i,j})$ used in this chapter (a proportional retirement age). We will argue that there are more connections between this objective and those found in the pension economics literature. Consider a world where the lifespan ($m_{i,j}$) varies significantly across individuals i and in a way that is correlated with observable socioeconomic status j. Consider that the objective of pension policy is equalising the ratio of the lifetime pension benefits to the lifetime pension contributions (i.e. equalising the pension actuarial fairness ratio, $afr_{i,j}$). Abstracting from the issue of death before reaching the retirement age, education length differences, career breaks, or demographic changes, that rate writes:

$$afr_{i,j} = \frac{m_{i,j} - ra_{i,j}}{ra_{i,j}} \times \theta_{i,j} \tag{3.7}$$

where $ra_{i,j}$ is the retirement age and $\theta_{i,j}$ is the ratio of pension benefits to pension contributions, which is functionally equivalent to the pension replacement rate. One way to equalise lifetime actuarial fairness ratios across individuals is to individualise the retirement ages $ra_{i,j}$. Another is to differentiate the replacement rate $\theta_{i,j}$ (by making it inversely proportional to the lifespan). Considering that $ra_{i,j} \equiv \alpha_{i,j} m_{i,j}$, the above expression becomes:

$$afr_{i,j} = \frac{1 - \alpha_{i,j}}{\alpha_{i,j}} \times \theta_{i,j} \tag{3.8}$$

Imagine, in addition, that we are in a Bismarckian pension system where benefits are strictly proportional to contributions (i.e. $\theta_{i,j} = \theta$, $\forall j \forall i$), then equalising the actuarial rate of fairness inevitably requires: $\alpha_{i,j} = \alpha$, $\forall j \forall i$. Thus the objective of equalising the share of life spent in retirement nests the objective of equalising lifetime actuarial fairness of Bismarckian pay-as-you-go pensions. And showing that the same result holds for Beveridgian pensions is straightforward.

3.4 Data construction

The data used hereafter consist of a simulation of the US distribution of lifespans, using the mortality rates assembled by Chetty et al. (2016). Their mortality rates are based on a sample of 1.4 billion observations from anonymised tax records, covering the years 1999 to 2014. Mortality data start at age 40 and are available either by gender and income percentile; or by gender, US state of residence and income quartile. Our simulations are based on the life table techniques of Chiang (1984) (see Section 3.8 for more details). In the end, we obtain simulations starting at 40 that can either be split by gender and income percentile or by gender, US state of residence and income quartile. For convenience of exposition, we refer to our simulation data on lifespans as the “population”.

Figure 3.1 displays two lifespan distributions; the dashed line corresponds to women in the 20^{th} income percentile, while the solid line corresponds to women in the 80^{th} percentile. More deaths occur at a younger age for women in the 20^{th} percentile. This is in line with the mortality gradient (i.e. the fact that people in lower socioeconomic status tend to die earlier than those in higher socioeconomic status). Two stylized facts emerge. First, the 20^{th} percentile distribution is less negatively skewed, capturing the negative impact of a lower income on life expectancy. Second, the distribution of lifespan is more dispersed for the 20^{th} percentile than for the 80^{th} percentile, echoing the presence of a higher lifespan dispersion among the lower socioeconomic status (see e.g. van Raalte et al., 2011).

3.5 Results

In this section, we report our results and analyse their robustness. We will first consider our index, with a proportional retirement age and no gap aversion. Then, we will test several specifications. We have normalized α at 1 in the tables and figures for clarity purpose. Therefore, the reader should multiply the values in tables and figures by α to have a particular retirement age.

Our first results appear in Table 3.1. It displays the retirement ages corresponding to different tagging policies. The tags used are gender, state of residence and income quantile. The retirement ages are different depending on the tag considered. For example, someone in the 25^{th} income percentile could retire $\alpha \times 2$ years earlier than the unique retirement age. Higher income percentiles retire later than the lower income; this is due to their higher life expectancy. The social planner sets the retirement age by income percentile. Therefore, a higher life expectancy (i.e. "average" lifespan) leads to higher retirement age. Nevertheless, this does not consider the fate of the short-lived individuals in the higher income percentiles. The aim of our index is to take into account the overall distribution of lifespan. Table 3.1 shows that 96.80 % of the gap remains after having differentiated the retirement age by income percentile. In other words, the introduction of 100 different retirement ages (one per income percentile) seems to contribute modestly to achieving the objective of a retirement age equal to the individualized one, as the gains are only 3.20% points compared to the uniform retirement policy. A further differentiation by gender and income percentile (thus 200 different retirement ages) only leads to a minor gain of 4.96%.

The small decrease of the index is due to the high variance of lifespan within groups.

In support of this statement, we have decomposed the variance and computed the Theil index[8] of the lifespan distribution (when the retirement ages are differentiated by gender and income percentile). The decomposition of the Theil index tells us that 95.22 % of the lifespan heterogeneity is attributable to the within socioeconomic status differences. The decomposition of the variance gives us a figure of 92.35 %. Those numbers are not surprising as van Raalte et al. (2012) have shown that differences of lifespan between education status (elementary, lower secondary, higher secondary and tertiary) cannot explain more than 4 % of the overall variance, the rest being within group differences. Together, these results show that socioeconomic status are far from being homogeneous.

3.5.1 Impact of gap aversion ($\beta \rightarrow 10$)

In the previous section, we assumed that β was equal to 1, meaning that the social planner was not averse to large gaps. The sensitivity of our results to the degree of gap aversion deserves attention. Table 3.2 displays the index as well as estimated values for both the unique and some differentiated retirement ages. A value of $\beta > 2$ is a bit extreme. However, computing the index and the retirement ages for a value of $\beta > 2$ is very informative to analyse further the different mechanisms behind our index.

Let us first consider β equal to 2. The unique retirement age decreases to $\alpha \times 83$ compared to $\alpha \times 85$ with $\beta = 1$. The ones differentiated by gender to $\alpha \times 81$ for men, compared to $\alpha \times 83$ with $\beta = 1$, and $\alpha \times 85$ for women, compared to $\alpha \times 88$ with $\beta = 1$. However, although retirement ages have changed, the values of the index do not improve that much, as they are now at 97.64 % for a retirement age differentiated by gender (compared to 98.32 % with $\beta = 1$), 92.35 % by gender and by percentile (compared to 95.04 % with $\beta = 1$), 99.53 % by state of residence (compared to 99.59 % with $\beta = 1$) and 92.57 % by state, gender and income quartile (compared to 95.08 % with $\beta = 1$). This indicates that, with a reasonable value of gap aversion, differentiating the retirement age does not lead to significant improvement(s). A system with 200 different retirement ages (by gender and percentile) reduces our index by only 7.65 %. The root of the problem remains in the shape of the distribution, which is too spread for the mean to be meaningful.

Three interesting results come into view in Table 3.2. First, a higher gap aversion implies a lower index. Second, the retirement age decreases as β increases. Finally, a higher aversion reduces the spread between the different retirement ages (e.g. between the one

[8] We use the formulas provided in the Additional File from van Raalte et al. (2012).

of the 25^{th} percentile and the one of the 75^{th} percentile). This stylized fact is noticeable in the comparison between Figure 3.2 and 3.3. Whereas Figure 3.2 displays a spread of $\alpha \times 4$ years across the different retirement ages by US State, Figure 3.3 shows a spread of only $\alpha \times 1$ year. The explanation of the first point is rather straightforward. The unique retirement age generates more gaps (and also more extreme ones) to the denominator of (3.4) than the differentiated retirement ages to its numerator. Therefore, as β goes up, the index's denominator grows more than its numerator; hence a negative relationship between the two. This is also intuitive: a social planner with a high gap aversion will care more about gaps compared to the situation of equal treatment and, therefore, be more prone to establish several retirement ages. The second feature (the decrease of the retirement age) stems from *i)* the very definition of gap aversion, larger gaps matter more than small ones, and *ii)* gaps being more frequent on the left- than on the right-hand side of the distribution (see Figure 3.4). The third point (the decrease of the spread between the retirement ages) is due to the difference of lifespan dispersion across income percentiles. Figure 3.5 shows that the distribution characterising the lifespan of men belonging to the 25^{th} income percentile is more dispersed than the one of women forming the 75^{th} percentile. It is well-documented in demography that lower-income percentiles display more lifespan dispersion (see e.g. van Raalte et al., 2011). As a consequence, the change of retirement age for low-income individuals is smaller due to the importance of right-hand side gaps. As a result, as one retirement age decreases more than the other, the spread between the retirement ages drops.

3.5.2 Increasing the number of ages of retirement

Another interesting question is the link between the increase of the number of different retirement ages envisaged by the planner and the decrease of the index. To answer this question, we have computed the index (see Figure 3.6) for 1 to 10 income brackets with $\beta = 1$.[9] We see that the marginal improvement is decreasing and, that the gain is closed to zero beyond 8 income brackets. Those results indicate that multiplying the number of retirement ages generates decreasing marginal benefits. Note that this result comforts us in the belief that there is a limited risk of moral hazard. An individual could try to change his position in the income distribution to modify his retirement age. However, if the social planner uses 8 income brackets (instead of the 100 percentiles), it will be relatively more difficult to change from one bracket to another.

[9] Two brackets mean that the retirement age is different for the people in the 1-50^{th} and the 51-100^{th} income percentiles; three brackets that it differs for people in the 1-33^{th}, 34-66^{th} and the 67-100^{th} income percentiles...

3.5.3 Different weights for positive versus negative gaps

So far, we have explored the sensitivity of our results to varying degrees of gap aversion. But that parameter assumes that positive and negative gaps are equally important. What if the planner cares more about positive gaps, in other words about those individuals who retire later than what their lifespan would command? To answer that question we modify (3.4) as follows:

$$I\left(\mathbf{m}\right)=\frac{\left(\sum_{j=1}^{k}\sum_{i=1}^{n_j}|\alpha m_{i,j}-\alpha\mu_j\left(\mathbf{m_j}\right)|^{\beta}|\, m_{i,j}\leq\mu_j\left(\mathbf{m_j}\right)\right)+\left(\sum_{j=1}^{k}\sum_{i=1}^{n_j}\sigma|\alpha m_{i,j}-\alpha\mu_j\left(\mathbf{m_j}\right)|^{\beta}|\, m_{i,j}\geq\mu_j\left(\mathbf{m_j}\right)\right)}{\left(\sum_{j=1}^{k}\sum_{i=1}^{n_j}|\alpha m_{i,j}-\alpha\mu(\mathbf{m})|^{\beta}|\, m_{i,j}\leq\mu(\mathbf{m})\right)+\left(\sum_{j=1}^{k}\sum_{i=1}^{n_j}\sigma|\alpha m_{i,j}-\alpha\mu(\mathbf{m})|^{\beta}|\, m_{i,j}\geq\mu(\mathbf{m})\right)} \tag{3.9}$$

The difference stems from the presence of σ that weights differently positive and negative gaps. In some sense, σ can be related to the poverty line, whose purpose is to "partition the population into two groups that we want to treat differently" (Cowell, 2016, p. 49). A value below 1 means that gaps corresponding to those who retire too early (in reference to their individualized retirement ages) weigh more than the gaps for those who retire too late. Table 3.3 shows the effect of various values σ on the retirement age (with β equal to 1). The retirement age decreases with σ. This result is intuitive; as the social planner cares more about the gaps for those who retire too late (in reference to their individualized retirement age) than too early, he lowers the retirement age. The extreme result is obtained when he does not care at all about the gaps of those who retire too early ($\sigma = 0$). In this case, the retirement age is set at $\alpha \times 40$ with no gap on the left. All remaining gaps are on the right, but the planner does not care about these. This situation is obviously not realistic.

The second question is that of the impact of σ on the index. The effect is rather small as suggested by Table 3.4. This is because the overall distribution of lifespans is not altered by the weighting parameter σ. This parameter changes the retirement age and the weight on some gaps; but the behaviour of the index remains primarily driven by the very high dispersion within each socioeconomic status.

3.5.4 Truncation

We have shown that our results are robust to gap aversion and to the extra weight put on positive gaps. Another extension is to go for *left-hand truncation* in terms of the age distribution. Retirement can only happen beyond a certain age. Therefore, one might argue that the individual who dies at the age of 40 or 41 should not be taken into account. Table 3.5 shows the computation of the index with different levels of truncation. Recall that, given our data, our benchmark results are *de facto* those with truncation at the age of 40. We now consider truncation at 55, 60 and 70. The tentative conclusion is that our results are robust to different degrees of left-hand side truncation. The retirement age logically rises (see Table 3.6) because the planner stops considering the fate of most short-lived individuals. But the values of our gap index remain relatively unaltered.

3.5.5 Going non-linear

Until now, we have shown that our results are robust to several specifications (gap aversion, truncation and different weights for positive/negative gaps). However, all those robustness checks were done under a proportional retirement age assumption. As a final robustness check, we consider two other specifications. The first is that the retirement age should be convex with respect to lifespan. The second is that it should be concave. Figure 3.7 shows those two specifications and Table 3.7 reports their results. We see that our results are robust to those specifications. Fundamentally, the index is driven by the dispersion of lifespan. Assuming a different retirement policy does not alter our results as long as the policy is a function of the lifespan of the individuals.

To sum up, the take-home message from this section is that gains obtained from retirement age differentiation tend to be small. It takes 200 different retirement ages to decrease our index by 5%. The introduction of gap aversion, the existence of a social planner weighing positive gaps higher than negative ones, left-hand truncation, or another retirement policy did not fundamentally alter our results. In more policy terms, this suggests that when policy-makers envisage differentiating the age of retirement across socioeconomic status, they should not underrate the importance of unaccounted lifespan heterogeneity. By focusing only on life expectancy differences (e.g. across socioeconomic status) they risk neglecting the distributions of lifespan *within* each of these categories, as well as the large overlaps between these. In a nutshell, this chapter reminds us that there are four kinds of individuals: short-lived with low socioeconomic status, long-lived with low socioeconomic status, short-lived with high socioeconomic status and long-lived with high socioeconomic status. Ideally, an egalitarian social planner would transfer resources from the long-lived to the short-lived, and from those in a higher socioeconomic status towards those in a lower one.

Before moving to the next section, we would like to discuss two last points. First, one could argue that we are wrong to consider only lifespan as a source of individual heterogeneity.

People also differ in many other aspects that are relevant for retirement policy. Some future pensioners, for instance, may have worked in more arduous jobs.[10] However, taking those other sources of heterogeneity into account would probably not invalidate our results. The overall heterogeneity would be larger than the one considered here, as it would comprise not only lifespan, but also occupation arduousness. However, unless the planner's capacity to tag gets boosted, estimates would point at even larger shares of unaccounted heterogeneity than those we compute here. Second, one may question the external validity of our results. Do they hold for European countries? The only way to be sure would be to replicate our analysis using European data on lifespan and socioeconomic status. However, we would posit that as life expectancy inequality is known to be higher and more socially determined in the United States than in e.g. Belgium or France (see e.g. Delavande and Rohwedder, 2011), tagging is probably more effective at accounting for lifespan heterogeneity in the US than in Europe. In other words, we expect tagging to be (slightly) less relevant in Europe than in the US.

3.6 Discussion

In the preceding sections, we have presented our results without discussing *in extenso* some of the normative principles underpinning our chapter. This section aims at filling that void. We focus on two important questions: that of the choice of assessing policy based on an *ex-post* or an *ex-ante* framework, and the choice to shape retirement policy with respect to individuals or to groups.

3.6.1 *Ex-post* or *ex-ante* equality?

An *ex-ante* framework assesses situations based on expectations (e.g. the probability of a lottery) while an *ex-post* assesses based on realizations (e.g. the results of the lottery). In our context, *ex-ante* implies using life expectancy (i.e. an expectation) and *ex-post* implies using lifespan (i.e. a realization). The existing empirical literature is quite ambiguous as to which of the perspectives should be adopted. It is not uncommon to read policy recommendations that are intrinsically *ex-ante* (focusing on life expectancy) from papers that are based on *ex-post* mortality data. Several papers in the theoretical literature emphasize the importance of using an *ex-post* approach. The statement is that "at the end of the day, what matters is what people achieved, not what they expected to achieve" (Fleurbaey et al., 2016, p. 201).

[10] For a discussion of the level of job arduousness across sectors and occupation, see Baurin and Hindriks (2019) and Chapter 2.

The argumentation is that individuals can only "eat" the (ex-post) results of the lottery, not its (ex-ante) distribution.

Let us explain the fundamental flaw of using an *ex-ante* approach when it comes to differentiating the retirement age. Assume that a social planner is egalitarian and based his thinking on an ex-ante framework. He knows that the life expectancy of individuals differs based on lifetime income. As stated by Fleurbaey et al. (2016, p. 201), "ex-ante egalitarianism that is based on average mortality statistics is not really ex-ante egalitarian if it fails to track individual's true life expectancy". So, the social planner has to take into account the lifetime income and, starting from a situation with a unique retirement age, he introduces a first differentiation. However, there is no justification why a social planner should only consider income. He should then, for example, further differentiate the retirement age according to the childhood circumstances as we know that they affect later morbidity (see e.g. Trannoy et al., 2010). But there is no reason why he should stop at that step, and he should then move on to further differentiation. The social planner's agenda will only be fulfilled when all factors influencing life expectancy have been taken into account. At that moment, he will have "track individual's true life expectancy". However, assuming *full and perfect knowledge* of the whole set of factors affecting life expectancy, our social planner will end up with an individualized retirement age, corresponding to the true lifespan of the individual.[11] This shows that a social planner who wants to differentiate the retirement age is fundamentally starting to switch from an ex-ante perspective to an ex-post one. Therefore, either one concludes that differences of lifespans should be taken into account (i.e. by differentiating the retirement age) and uses an *ex-post* framework, or one concludes that differences of lifespan should not be taken into account and enforce a unique retirement age.

3.6.2 Across individuals or groups?

The second choice to make is to assess the difference across individuals or across groups. The empirical literature has focused on differences across groups, whereas this chapter focuses on individuals. The reason comes from the impossibility of putting someone *uncontroversially* in a particular group due to the non-existence of "natural" categories. Those created by

[11] Fishkin (2014) uses a similar argumentation when he explains the problem of achieving equality of opportunity. He argues that we have to withdraw every differences between individuals if we want to achieve equality of opportunity between them. Equality of opportunity would not be achieved if we still leave only one slight difference (e.g. in some genes). The same argumentation applies in our case. The social planner has to take into account every characteristic affecting lifespan if he wants to be *truly* egalitarian.

statisticians will always be somehow arbitrary, undermining their legitimacy for public policy. One might raise the point that a percentile is not created by statisticians, but exists naturally in the reality (as it comes from the distribution). True. But the statistician or the policy-makers eventually decides to tag using deciles instead of percentiles. An individual can always object that the level of precision is too low or too high and places him in the wrong group. Moreover, for an individual what matters is the situation and not what may have caused it (Murray, 2001).[12]

As such, it makes no difference for an individual if the lifespan is smaller due to some between- or within-group factors; what matters to him is his lifespan and how it compares with the lifespans of other individuals. Nevertheless, some (e.g. Gakidou et al., 2000) argue that differences in health across groups are often more informative than differences across individuals because the former removes the component due to luck.[13] This is true. Differences in average health between socioeconomic status show social health inequalities. But, the question is to know if the differences are sufficiently informative for pension policies. If the normative criterion is that an individual dying earlier should retire earlier, the heterogeneity within group makes undesirable to use groups instead of individuals. As explained in the introduction, Phelps (1972) shows in his seminal work that a decision-maker, with time constraints, could base his decision on average characteristics and, by doing so, some high-performing members belonging to an under-performing group are discriminated against. The same arises when the social planner focuses only on life expectancy: short-lived individuals with a high life expectancy are penalized because the social planner does not take the time to look deeper into each group.

3.7 Conclusion

Lifespan heterogeneity has at least three detrimental consequences for pension systems. First, it decreases the lifetime progressivity of the pension system; second, it does not price correctly the insurance for the risk of living a long life and, third, it creates unequal lengths of retirement. In this chapter, we have primarily considered the third consequence. To address

[12] In this chapter, we do not look at responsibility. Indeed, it can matter if the outcome is due to personal responsibility or to bad luck. We only discuss situations where the outcome is from different causes out of control of the individual.

[13] Differences across individuals can be due to random elements. However, average differences across groups remove the random component and so, the difference reflects the impact of being in a particular group on health. If the groups are smokers vs. non-smokers, the difference of health between them reflects the impact of smoking.

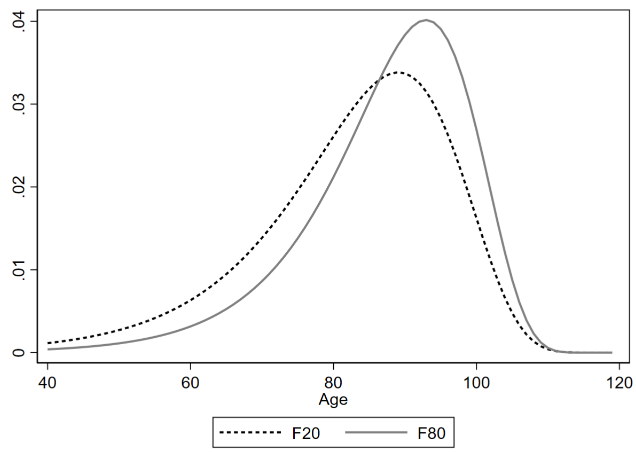
it, the policy recommendation is often to differentiate the retirement age based on the socioeconomic life expectancy gradient. However, one caveat of this policy recommendation is its focus on differences of life expectancy, to the neglect of the full distribution of lifespans. In this chapter, we show that differentiating the retirement age by socioeconomic status still leaves a large share of the total heterogeneity of lifespan unaccounted for. This is of particular importance for the third point. Differentiating the retirement age to help everyone enjoy a given amount/percentage of year in retirement is not possible if governments are not able to correctly tag individuals.

The take-home message is that pension policy is relatively limited in its capacity to optimally differentiate the retirement age to help everyone enjoy some years of retirement. At the individual level, many factors are causing enormous variations in lifespans. Although state, gender and lifetime income are important predictors of lifespan, using them to systematically differentiate retirement age would largely fail to account for a large portion of distribution of lifespan in the population. Moreover, lifespan distributions across socioeconomic status overlap. We have analysed various scenarios of differentiation. For all of them, the reduction of our index turns out to be relatively small, including when we allow for up to 200 different retirement ages. The conclusion is robust to several specifications (higher gap aversion, different weights for positive/negative gaps, truncation and different retirement policies).

This chapter shows that the gains that may be achieved by abandoning a unique retirement age policy are maybe not as strong as it is often supposed, due to the imperfect information faced by the social planner. Differentiating the age of retirement by gender and income brackets would account for some of the inequalities of lifespan. However, it would not be sufficient to solve the overall problem of accounting for lifespan differences in the population. The problem of heterogeneity within socioeconomic status is not only relevant for pension policy. Average health also differs across socioeconomic status, but with an important heterogeneity within. Deaton (2002) already emphasizes that health policy should directly target sick people, rather than income groups. Policy-makers could of course double down on their efforts to better predict the lifespan of individuals. Using the parents' lifespan could be an interesting research as the literature has already shown their importances (see e.g. Gudmundsson et al., 2000; Vågerö et al., 2018).

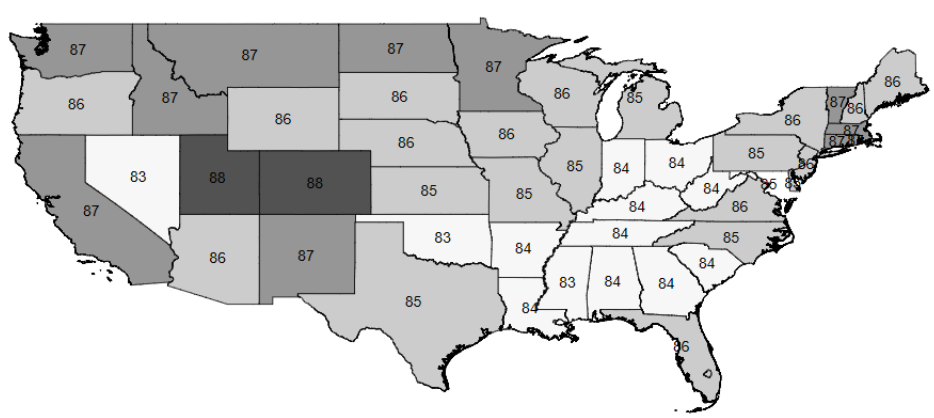
We expect the question of unfairness of the pension system due to (in some cases growing) lifespan heterogeneity to remain a very hot topic in the future. We also anticipate that people will keep arguing in favour or against retirement age differentiation. Those who oppose to retirement age differentiation might read our results as a proof that it should be abandoned. We are not so sure. Differentiating the retirement age could be done for several reasons and this chapter has only looked at one (helping everyone to enjoy some time in retirement). The unaccounted difference of lifespan should still be used to support the historical insurance role of pensions. The only thing we confidently say is that the benefits of differentiation are not as large as generally assumed by those who advocate it, essentially because lifespan heterogeneity is huge and difficult to account for. A definite answer about the intrinsic interest of retirement age differentiation calls for more research. First, further works should explore what happens when people differ in terms of lifespan, but also of income. Second, a richer model, incorporating the cost of tagging (moral hazard, administrative cost...) should be developed to quantify the *net* gains of differentiation. Third, research should also consider the possibility of using a flexible retirement age, where individuals (and not just the planner) choose the retirement age, based on their own evaluation of what their lifespan might be. Fourth, more out-of-the-box ideas could also be studied like the one of a "reverse retirement" introduced by Ponthiere (2020)[14] or that of partial de-annuitization explored by Vandenberghe (Forthcoming).

[14] Ponthiere (2020) considers a model where individuals start their life in retirement (and thus "all" receive their pensions) before moving into work.



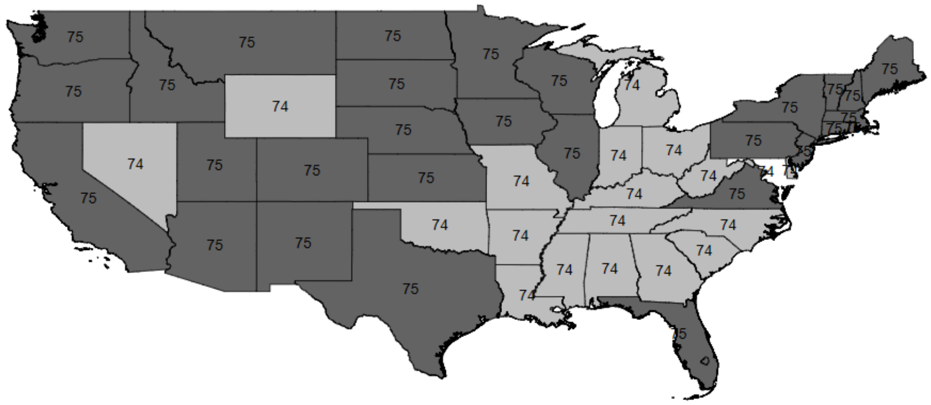
The figure shows the simulation of US lifespan distribution for women in the 20^{th} and 80^{th} income percentile. Simulations are done using the mortality rates provided by Chetty et al. (2016). The lifespan distribution of the women with a higher income is more negatively skewed which reflects their higher life expectancy. The lifespan of the women with a lower income is more dispersed which is a stylized demographic fact.

Figure 3.1: Distribution of lifespan for women in the 20^{th} and the 80^{th} percentile



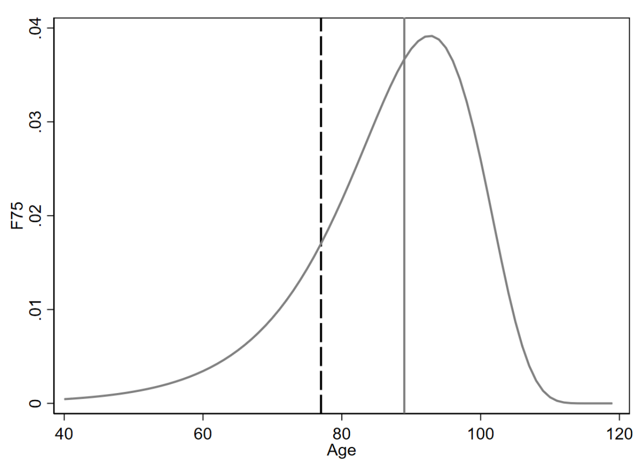
The figure shows the retirement age by state of residence with β and α equal to 1. Simulations use the mortality rates provided by Chetty et al. (2016).

Figure 3.2: Impact of differentiating the retirement age by state (β and $\alpha = 1$)



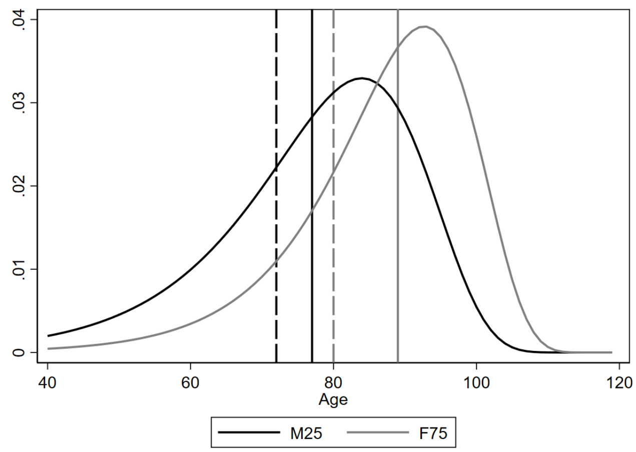
The figure shows the retirement age by state of residence with β equal to 10 (and α equal to 1). Simulations use the mortality rates provided by Chetty et al. (2016).

Figure 3.3: Impact of differentiating the retirement age by state ($\beta = 10$, $\alpha = 1$)



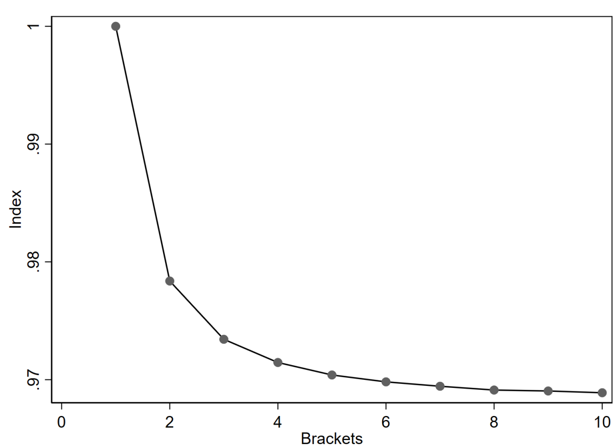
The figure shows the decrease in the retirement age when β increases. Simulations use the mortality rates provided by Chetty et al. (2016). The retirement age (with α equal to 1) is the solid line when β equal 1 and the dashed one when β equal 10.

Figure 3.4: Explanation of the decrease of the retirement age (Women, 75^{th} percentile)



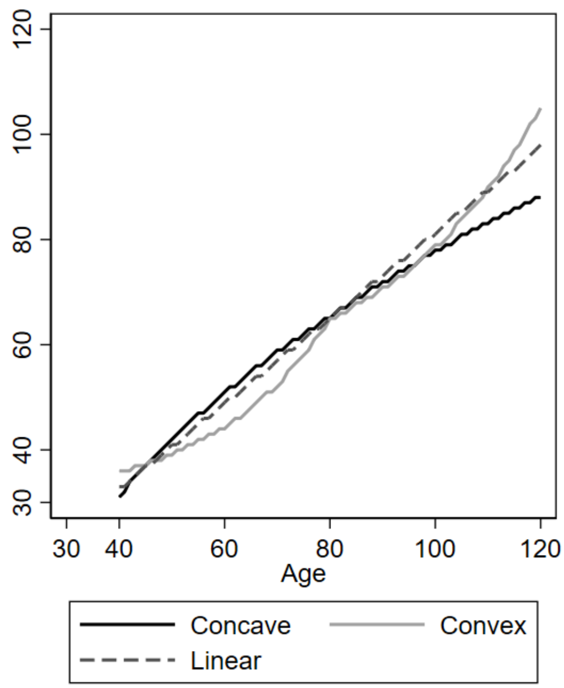
The figure shows the decrease in the spread between the retirement ages when β increases. Simulations are done using the mortality rates provided by Chetty et al. (2016). The retirement age for the men in the 25^{th} income percentile (with α equal to 1) is the solid black line when β equal 1 and the dashed black one when β equal 10. The retirement age for the women in the 75^{th} income percentile (with α equal to 1) is the solid grey line when β equal 1 and the dashed grey one when β equal 10.

Figure 3.5: Explanation of the narrowing spread



The graph shows the value of the index with the increase in the number of income brackets. One bracket means that there is only one retirement age, two brackets means that the retirement age is different for the individuals having their income in the 1-50^{th} percentile and in the 51-100^{th}, three brackets means that it is differentiated between the individuals in the 1-33^{th}, 34-66^{th} and 67-100^{th} income percentile; and so on.

Figure 3.6: Decrease of the index with the number of income bracket ($\beta = 1$)



The figure shows the three different specifications of the retirement ages. All specifications respect the principle of a lower retirement age for shorter lifespan. The first specification is concave and is obtained as follows: $\delta\left(m_{i,j}\right) = -10 + 10 * \sqrt{m_{i,j} - 23}$. The second is linear (i.e. proportional) and is obtained as follows: $\delta\left(m_{i,j}\right) = 81.25\,\% \times m_{i,j}$. The third is convex and is obtained as follows: $\delta\left(m_{i,j}\right) = e^{m_{i,j}/22.5} + 30$ if $m_{i,j} \leq 80$ and $\delta\left(m_{i,j}\right) = e^{m_{i,j}/30} + 50.5$ if $m_{i,j} > 80$. All specifications have a retirement age of 65 for a lifespan of 80.

Figure 3.7: Retirement ages for three different specifications

Index						
	By gender	By percentile	By gender & percentile	By state	By state & gender	By state, gender & quartile
	98.32 %	96.80 %	95.04 %	99.59 %	97.92 %	95.08 %

Retirement age ($\alpha = 1$)												
Unique	Male	Female	25^{th}	75^{th}	M, 25^{th}	F, 75^{th}	Min	Nev	Min, M	Nev, F	Min, M, 1^{st}	Nev, F, 4^{th}
85	83	88	83	87	80	89	87	83	85	85	79	88

The table provides the value of the index when β equal 1. The index is done for tagging by gender; by income percentile; by gender and percentile; by state of residence; by state of residence and gender; by state of residence, gender and income quartile. The line below shows different retirement ages depending on the policy (with α equal to 1). The retirement ages provided are unique, gender-specific, for individuals in the 25^{th} income percentile, for individuals in the 75^{th} income percentile, for men in the 25^{th} income percentile, for women in the 75^{th} income percentile, for residents in Minnesota, for residents in Nevada, for men in Minnesota, for women in Nevada, for men in Minnesota and in the 1^{st} income quartile, for women in Nevada in the 4^{th} income quartile.

Table 3.1: Index and retirement age for several tags ($\beta = 1$)

β	Index					
	By gender	By percentile	By gender & percentile	By state	By state & gender	By state, gender & quartile
1	98.32 %	96.80 %	95.04 %	99.59 %	97.92 %	95.08 %
2	97.64 %	94.97 %	92.35 %	99.53 %	97.15 %	92.57 %
3	96.89 %	93.38 %	90.16 %	99.38 %	96.40 %	90.54 %
4	96.72 %	92.54 %	88.83 %	99.47 %	96.03 %	89.30 %
5	95.88 %	91.68 %	87.56 %	99.41 %	95.41 %	88.18 %
10	94.39 %	90.18 %	84.30 %	99.07 %	93.17 %	85.14 %

β	Retirement age ($\alpha = 1$)												
	Unique	Male	Female	25^{th}	75^{th}	M, 25^{th}	F, 75^{th}	Min	Nev	Min, M	Nev, F	Min, M, 1^{st}	Nev, F, 4^{th}
1	85	83	88	83	87	80	89	87	83	85	85	79	88
2	83	81	85	80	85	78	86	84	81	82	83	77	86
3	81	79	82	79	83	76	84	82	79	80	81	75	84
4	79	77	80	77	81	75	82	80	78	79	79	74	82
5	78	76	79	76	79	74	81	79	77	77	78	74	80
10	75	73	76	74	76	72	77	75	74	74	75	72	76

The table provides the value of the index with different values of β. The index is done for tagging by gender; by income percentile; by gender and percentile; by state of residence; by state of residence and gender; by state of residence, gender and income quartile. The lines below show different retirement ages depending on different values of β (with α equal to 1). The retirement ages provided are the unique, gender-specific, for individuals in the 25^{th} income percentile, for individuals in the 75^{th} income percentile, for men in the 25^{th} income percentile, for women in the 75^{th} income percentile, for residents in Minnesota, for residents in Nevada, for men in Minnesota, for women in Nevada, for men in Minnesota and in the 1^{st} income quartile, for women in Nevada in the 4^{th} income quartile.

Table 3.2: Index and retirement age for various values of β

σ	Unique	By gender		By percentile		By gender & percentile		By state		By state & gender		By state, gender & quartile	
		Male	Female	25^{th}	75^{th}	M, 25^{th}	F, 75^{th}	Min	Nev	Min, M	Nev, F	Min, M, 1^{st}	Nev, F, 4^{th}
1	85	83	88	83	87	80	89	87	83	85	85	79	88
0.75	83	81	85	80	85	77	87	85	81	83	83	76	86
0.5	80	77	82	77	82	74	84	77	81	79	80	72	83
0.25	73	71	76	70	76	68	78	71	75	73	74	65	78
0	40	40	40	40	40	40	40	40	40	40	40	40	40

The table provides the retirement ages with different values of σ. The retirement ages provided are the unique, gender-specific, for individuals in the 25^{th} income percentile, for individuals in the 75^{th} income percentile, for men in the 25^{th} income percentile, for women in the 75^{th} income percentile, for residents in Minnesota, for residents in Nevada, for men in Minnesota, for women in Nevada, for men in Minnesota and in the 1^{st} income quartile, for women in Nevada in the 4^{th} income quartile. σ equals to 1 is our benchmark from previous table.

Table 3.3: Retirement age by σ (β and $\alpha = 1$)

σ/β	By gender			By percentile			By gender & percentile		
	1	2	5	1	2	5	1	2	5
1	98.32 %	97.64 %	95.88 %	96.80 %	94.97 %	91.68 %	95.04 %	92.35 %	87.56 %
0.75	98.48 %	97.65 %	96.33 %	96.70 %	94.71 %	91.73 %	95.06 %	92.18 %	87.67 %
0.5	98.55 %	97.72 %	96.22 %	96.42 %	94.41 %	91.50 %	94.96 %	92.00 %	87.54 %
0.25	98.78 %	97.86 %	96.50 %	96.09 %	93.91 %	91.29 %	94.89 %	91.74 %	87.50 %
0	0.00 %	0.00 %	0.00 %	0.00 %	0.00 %	0.00 %	0.00 %	0.00 %	0.00 %
σ/β	By state			By state & gender			By state, gender & quartile		
	1	2	5	1	2	5	1	2	5
1	99.59 %	99.53 %	99.41 %	97.92 %	97.15 %	95.41 %	95.08 %	92.57 %	88.18 %
0.75	99.65 %	99.48 %	99.48 %	98.11 %	97.13 %	95.61 %	95.15 %	92.38 %	88.26 %
0.5	99.65 %	99.51 %	99.46 %	98.25 %	97.24 %	95.61 %	95.14 %	92.28 %	88.18 %
0.25	99.69 %	99.48 %	99.45 %	98.48 %	97.36 %	95.77 %	95.16 %	92.10 %	88.16 %
0	0.00 %	0.00 %	0.00 %	0.00 %	0.00 %	0.00 %	0.00 %	0.00 %	0.00 %

The table provides the index with different values of σ and β. σ varies from 0 to 1 and β takes the value of 1, 2 and 5. σ equal to 1 is our benchmark from previous table.

Table 3.4: Index by σ and by β

Truncation	By gender	By percentile	By gender & percentile	By state	By state & gender	By state, gender & percentile
40	98.32 %	96.80 %	95.04 %	99.59 %	97.92 %	95.08 %
55	98.32 %	97.13 %	95.33 %	99.66 %	97.95 %	95.32 %
60	98.30 %	97.22 %	95.42 %	99.57 %	97.83 %	95.36 %
70	98.28 %	97.67 %	95.88 %	99.64 %	97.87 %	95.85 %

The table provides the index with different level of truncation. Truncation at 40 is our benchmark from previous table, truncation at 55, 60, 70 are arbitrary values of truncation.

Table 3.5: Index with different level of truncation ($\beta = 1$)

		By gender		By percentile		By gender & percentile		By state		By state & gender		By state, gender & quartile	
Truncation	Unique	Male	Female	25^{th}	75^{th}	M, 25	F, 75	Min	Nev	Min, M	Nev, F	Min, M, 1^{th}	Nev, F, 4^{th}
40	85	83	88	83	87	80	89	87	83	85	85	79	88
55	86	84	88	83	88	81	89	88	84	86	86	80	89
60	86	84	88	84	88	81	89	88	84	86	86	81	89
70	88	86	89	86	89	84	90	89	86	87	87	84	90

The table provides the retirement ages with different level of truncation. The retirement ages provided are the unique, gender-specific, for individuals in the 25^{th} income percentile, for individuals in the 75^{th} income percentile, for men in the 25^{th} income percentile, for women in the 75^{th} income percentile, for residents in Minesotta, for residents in Nevada, for men in Minesotta, for women in Nevada, for men in Minesotta and in the 1^{st} income quartile, for women in Nevada in the 4^{th} income quartile. Truncation at 40 is our benchmark from previous table, truncation at 55, 60, 70 are arbitrary values of truncation.

Table 3.6: Retirement ages with different level of truncation (β and $\alpha = 1$)

Index													
		By gender		By percentile		By gender & percentile		By state		By state & gender		By state, gender & quartile	
Concave		98.57 %		97.06 %		95.34 %		99.79 %		98.12 %		95.36 %	
Linear		98.32 %		96.80 %		95.04 %		99.59 %		97.92 %		95.08 %	
Convex		98.87 %		97.71 %		96.27 %		99.83 %		98.61 %		96.25 %	
Retirement age													
	Unique	Male	Female	25^{th}	75^{th}	M, 25^{th}	F, 75^{th}	Min	Nev	Min, M	Nev, F	Min, M, 1^{st}	Nev, F, 4^{th}
Concave	69	67	71	67	70	65	71	70	67	69	69	65	71
Linear	69	67	72	67	71	65	72	71	67	69	69	64	72
Convex	68	66	69	66	69	65	70	69	66	68	68	63	69

The table provides the value of the index when β equal 1 for different specifications of the retirement age policy (concave/linear/convex). The index is done for tagging by gender; by income percentile; by gender and percentile; by state; by state and gender; by state, gender and income quartile. The lines below show different retirement ages depending on the policy. The retirement ages provided are the unique, gender-specific, for individuals in the 25^{th} income percentile, for individuals in the 75^{th} income percentile, for men in the 25^{th} income percentile, for women in the 75^{th} income percentile, for residents in Minesotta, for residents in Nevada, for men in Minesotta, for women in Nevada, for men in Minesotta and in the 1^{st} income quartile, for women in Nevada in the 4^{th} income quartile.

Table 3.7: Index and retirement age for several policies ($\beta = 1$)

3.8 Appendix

Appendix A: The parameter $(\mu(\mathbf{m}), \mu_j(\mathbf{m_j}))$

The social planner desires to minimize the sum of the gaps between the retirement age and the lifespan of the observations in each subset/the entire set. Let us study $\mu(\mathbf{m})$:

$$\sum_{i=1}^{n} |\alpha m_i - \alpha\mu(\mathbf{m})|^{\beta} \tag{3.A1}$$

The derivative of (3.A1) with respect to $\mu(\mathbf{m})$ is:

$$\sum_{i=1}^{n} -\alpha\beta|\alpha m_i - \alpha\mu(\mathbf{m})|^{\beta-2}(\alpha m_i - \alpha\mu(\mathbf{m})) \tag{3.A2}$$

If β is odd, then the root is located at the following condition:

$$\sum_{i=1}^{n} |\alpha m_i - \alpha\mu(\mathbf{m})|^{\beta-1}\frac{(\alpha m_i - \alpha\mu(\mathbf{m}))}{|\alpha m_i - \alpha\mu(\mathbf{m})|} = 0 \tag{3.A3}$$

Condition (3.A3) states that μ is the median when β equals 1. If β is odd and above 1, there exists no statistical name to the condition (3.A3) and the social planner finds the root by computation and by applying condition (3.A3). For an even value of β, the root is located at the following condition:

$$\sum_{i=1}^{n} (\alpha m_i - \alpha\mu(\mathbf{m}))^{\beta-1} = 0 \tag{3.A4}$$

Condition (3.A4) states that μ is the mean when β equals 2. There exists no statistical name to the condition (3.A4) when β is even and above 2 and the social planner finds the root by computation and by applying condition (3.A4).

The same principles apply for $\mu_j(\mathbf{m_j}), \forall j$.

Appendix B: Data construction

Our data have been constructed based on the life table technique detailed in Chiang (1984) and on the mortality rates provided by Chetty et al. (2016). The life-table method starts with a normalized population (called the "radix") and, at each interval of time, a fraction of the population "died" based on the empirically observed mortality rate. The division of the total years lived beyond age m by the population alive at that age gives the life expectancy of the population at age m. Our interest lies in the number of people dying at each age, which provides us our lifespan distribution. We used the mortality rates provided by Chetty et al. (2016)[15] which they computed based on a sample of 1,4 billion observations from anonymised tax records between 1999 and 2014. Their mortality rates are the empirical ones between 40 and 75 years old, then they computed an interpolation using the Gompertz curve for the ages between 76 and 90 and finally, used the income-independent mortality rates based on NCHS and SSA data for the ages between 91 and 120. Figure 3.A1 shows the lifespan distribution for women in the 20$^{\text{th}}$ and in the 80$^{\text{th}}$ percentile. One can notice the presence of a spike at 91, which is the result of the change from the Gompertz curve to the NCHS-SSA mortality rate. It is more important for the 80$^{\text{th}}$ percentile because there are more person alive at 91 in it than in the 20$^{\text{th}}$ and the change to the NCHS-SSA mortality rate is, therefore, more reflected in it.

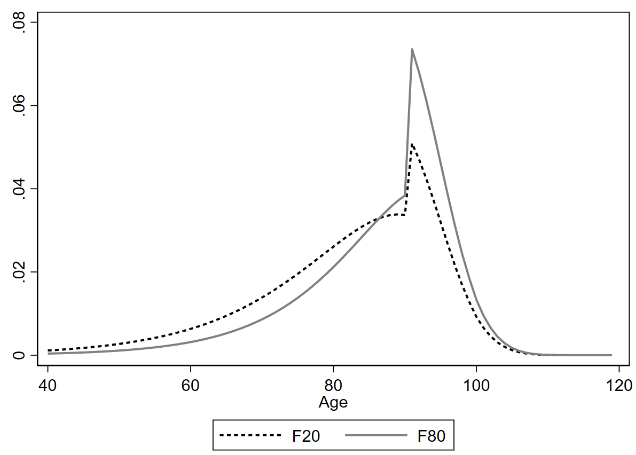


Figure 3.A1: Distribution of lifespan for women in the 20$^{\text{th}}$ and the 80$^{\text{th}}$ percentile

The presence of this spike could raise the controversy of its importance for the results that we obtain. As a robustness test, we have also computed the distribution using the Gompertz curve only. There is some empirical debate about the limit age until which it can be used; for example, Gavrilov and Gavrilova (2011) find that it could be extended until 105 without any difficulty. Above 105, its relevance is difficult to test due to the small number of observations and the quality of the data.[16] As there are not many individuals living older than 105, extending the Gompertz curve until the end is not a strong assumption. In the main part of the chapter, we use graphs based on the Gompertz curve for reading easiness

[15]They provided adjusted and non-adjusted race mortality rate, we use the non-adjusted to approach more the real distribution.

[16]An individual older than 105 has his birth date at the beginning of the 1900's and the records are often of poor quality. For example, Gavrilov and Gavrilova (2011) showed that the ratio male-female observed in their data above 105 could not be the true one.

(no spike), but the results reported are those using the Chetty et al. (2016) assumptions. Robustness of results using only the Gompertz curve could be found in Appendix C. A little limitation of our database is that we could not decompose lifespan by months. We think that it would only change slightly our results as the main part is already captured by using years. There remains some seasonality of death,[17] but this should not impact dramatically our results. Another limitation of our study is that we have to take as exogenous the lifespan distribution; although some papers (see e.g. Dave et al., 2008) have shown that retirement has an effect on the health of individuals.

Appendix C: Table with the data using only the Gompertz curve

3.8.1 Index and retirement age for various values of β

β	Index					
	By gender	By percentile	By gender & percentile	By state	By state & gender	By state, gender & quartile
1	98.44 %	97.02 %	95.36 %	99.62 %	98.07 %	95.43 %
2	97.22 %	94.53 %	91.58 %	99.29 %	96.51 %	91.75 %
3	96.27 %	92.71 %	88.69 %	99.15 %	95.36 %	89.03 %
4	95.24 %	91.46 %	86.46 %	98.81 %	94.08 %	86.70 %
5	94.40 %	90.69 %	84.78 %	98.67 %	93.06 %	85.00 %
10	89.79 %	89.20 %	78.85 %	97.55 %	87.95 %	79.19 %

β	Retirement age ($\alpha = 1$)											
	Unique	Male	Female	25^{th}	75^{th}	M, 25^{th}	F, 75^{th}	Min	Nev	Min, M	Nev, F	Min, M, 1^{st}	Nev, F, 4^{th}
1	85	83	88	83	87	80	89	87	83	85	85	79	88
2	83	81	86	81	85	78	87	85	81	83	83	77	87
3	82	80	84	79	84	77	85	83	80	81	82	76	85
4	80	78	82	78	82	76	84	82	78	80	80	75	83
5	79	77	81	77	81	75	82	80	77	79	79	74	82
10	77	75	78	75	77	73	78	77	75	76	76	73	78

Table 3.A1: Index and retirement age for various values of β

[17]The seasonality of death is not felt uniformly across the population; old people and those at a low socioeconomic level tend to be more impacted by it (Rau, 2006).

3.8.2 Retirement age by σ (β and $\alpha = 1$)

σ	Unique	By gender		By percentile		By gender & percentile		By state		By state & gender		By state, gender & quartile	
		Male	Female	25^{th}	75^{th}	M, 25^{th}	F, 75^{th}	Min	Nev	Min, M	Nev, F	Min, M, 1^{st}	Nev, F, 4^{th}
1	85	83	88	83	87	80	89	87	83	85	85	79	88
0.75	83	81	85	80	85	77	87	85	81	83	83	76	86
0.5	80	77	82	77	82	74	84	81	77	79	80	72	83
0.25	73	71	76	70	76	68	78	75	71	73	74	65	78
0	40	40	40	40	40	40	40	40	40	40	40	40	40

Table 3.A2: Retirement age by σ (β and $\alpha = 1$)

3.8.3 Index by σ and by β

σ/β	By gender			By percentile			By gender & percentile		
	1	2	5	1	2	5	1	2	5
1	98.44 %	97.22 %	94.40 %	97.02 %	94.53 %	90.69 %	95.36 %	91.58 %	84.78 %
0.75	98.57 %	97.37 %	94.46 %	96.89 %	94.43 %	90.45 %	95.35 %	91.62 %	84.69 %
0.5	98.62 %	97.47 %	94.70 %	96.59 %	94.13 %	90.48 %	95.20 %	91.50 %	84.95 %
0.25	98.83 %	97.67 %	95.01 %	96.23 %	93.76 %	90.33 %	95.07 %	91.44 %	85.17 %
0	0.00 %	0.00 %	0.00 %	0.00 %	0.00 %	0.00 %	0.00 %	0.00 %	0.00 %
σ/β	By state			By state & gender			By state, gender & quartile		
	1	2	5	1	2	5	1	2	5
1	99.62 %	99.29 %	98.67 %	98.07 %	96.51 %	93.06 %	95.43 %	91.75 %	85.00 %
0.75	99.68 %	99.43 %	98.47 %	98.22 %	96.78 %	93.03 %	95.45 %	91.86 %	84.94 %
0.5	99.67 %	99.42 %	98.76 %	98.33 %	96.89 %	93.43 %	95.38 %	91.83 %	85.25 %
0.25	99.70 %	99.44 %	98.86 %	98.54 %	97.14 %	93.82 %	95.33 %	91.86 %	85.58 %
0	0.00 %	0.00 %	0.00 %	0.00 %	0.00 %	0.00 %	0.00 %	0.00 %	0.00 %

Table 3.A3: Index by σ and by β

3.8.4 Index with different levels of truncation ($\beta = 1$)

Truncation	By gender	By percentile	By gender & percentile	By state	By state & gender	By state, gender & percentile
40	98.44 %	97.02 %	95.36 %	99.62 %	98.07 %	95.43 %
55	98.45 %	97.35 %	95.67 %	99.69 %	98.12 %	95.70 %
60	98.44 %	97.45 %	95.77 %	99.61 %	98.02 %	95.76 %
70	98.47 %	97.89 %	96.23 %	99.68 %	98.12 %	96.28 %

Table 3.A4: Index with different levels of truncation ($\beta = 1$)

3.8.5 Retirement ages with different levels of truncation (β and α = 1)

		By gender		By percentile		By gender & percentile		By state		By state & gender		By state, gender & quartile	
Truncation	Unique	Male	Female	25^{th}	75^{th}	M, 25	F, 75	Min	Nev	Min, M	Nev, F	Min, M, 1	Nev, F, 4
40	85	83	88	83	87	80	89	87	83	85	85	79	88
55	86	84	88	83	88	81	89	88	84	86	86	80	89
60	86	84	88	84	88	81	89	88	84	86	86	81	89
70	88	86	89	86	89	84	90	89	86	87	87	84	90

Table 3.A5: Retirement ages with different levels of truncation (β and $\alpha = 1$)

3.8.6 Index and retirement age for several policies ($\beta = 1$)

Index						
	By gender	By percentile	By gender & percentile	By state	By state & gender	By state, gender & quartile
Concave	98.66 %	97.23 %	95.59 %	99.81 %	98.24 %	95.65 %
Linear	98.44 %	97.02 %	95.36 %	99.62 %	98.07 %	95.43 %
Convex	98.96 %	97.87 %	96.52 %	99.85 %	98.72 %	96.54 %

Retirement age													
	Unique	Male	Female	25^{th}	75^{th}	M, 25^{th}	F, 75^{th}	Min	Nev	Min, M	Nev, F	Min, M, 1^{st}	Nev, F, 4^{th}
Concave	69	67	71	67	70	65	71	70	67	69	69	65	71
Linear	69	67	72	67	71	65	72	71	67	69	69	64	72
Convex	68	66	69	66	69	65	70	69	66	68	68	63	69

Table 3.A6: Index and retirement age for several policies ($\beta = 1$)

Conclusion

This thesis contributes to the public economics and the economics of ageing literature – at a moment when rapid population ageing calls for significant reforms of pension systems. It focuses on the problem of heterogeneity among current and prospective retirees and its implication for pension policy. Different kinds of heterogeneity are considered. Chapter 1 focuses on the heterogeneity in terms of individuals' age at the time of the reform. Chapter 2 examines the heterogeneity about the occupation performed during the career. Chapter 3 focuses on a third kind of heterogeneity: the lifespan of individuals.

The heterogeneity among the population is an important factor to take into account when designing pension policies. It should not be overlooked. Otherwise, there exists a threat of creating inequitable pension systems and, by doing so, putting their social legitimacy at risk. Therefore, criteria of equity are important when thinking about pension policy. In Chapter 1, the pension reform is analysed through the lens of intergenerational equity. Ideally, a pension reform of a pay-as-you-go system should distribute the costs evenly across all cohorts. However, it is shown that, depending on the parameter used to adjust the pension system, it could be far from true. In particular, in the context of Belgium, a reform balancing the pension system over the period 2020-2100 through the accrual rate would put 85 % of the costs of the reform on the shoulders of the youngest half of population. An indexation reform would be better as it puts only 65 % of the costs on the youngest half of the population. However, it is shown that the outcome of a democratic vote would be in favour of the accrual reform due to the high weight of the older cohorts. Therefore, there exists a tradeoff between democracy and equality. This result is robust to the inclusion of altruism for the next generation. In Chapter 2 and Chapter 3, the equity considered is across individuals. This criterion complements the intergenerational one. Individuals experience different working conditions and that can be harmful to their health. It is shown that a ranking of occupation arduousness could be inferred from the health of individuals at old age using the 7$^{\text{th}}$ wave of the SHARE database. Then, based on the policy of career length differentiation rather than retirement age differentiation,[1] it is shown that the difference required to compensate for the career arduousness could be quite high – up to 15 years. It is also demonstrated that career arduousness is not the main determinant of bad health at old age, but that childhood conditions are more important. The equity across individuals regarding the lifespan is considered in Chapter 3. Individuals differ in the number of years that they live and this is an important point for pension policy. The literature has already analysed this problem based on life expectancy. In this chapter, it is shown that there exists a lot of lifespan differences inside socioeconomic status (based on US socioeconomic lifespan distributions simulated from the data collected by Chetty et al. (2016)). Moreover, the lifespan distributions tend to overlap across socioeconomic status. The key finding is that using socioeconomic status to differentiate the retirement age is far from perfect. Differentiating the retirement age would account for some of the inequalities of lifespan. However, it may not be sufficient to achieve full interindividual equity. As we see, heterogeneity can impact pension systems in various ways.

A lot of take-home messages should be remembered from this thesis. First and foremost, heterogeneity is important when designing pension policies. It has only been analysed in three different ways in this thesis, and there remain a lot of other dimensions to investigate (across sex, across self-employed vs. employees,...). Designing an equitable pension system can only be done if heterogeneity is correctly considered and investigated. Second, population ageing mechanically increases the electoral weight of older cohorts and this leads to reforms that can be detrimental to the youth - with the potential to impose inequitable reforms on the young. As a result, some legal safeguards against majority voting when it involves putting an (inequitable) pressure on the minority should be installed. For example, a minimum accrual rate could be imposed to make the indexation adjustment necessary for any reform. The major problem comes from the grandfather clause which does not allow to make retrospective adjustment. Withdrawing it would enable better sharing of the pension reform costs across generations. Third, working conditions are heterogeneously harmful to health; but they are not the only driver of bad health at old age. Preventive policies in childhood should be more emphasized in the public debate to permit everyone to arrive at adulthood in good health. Pension systems may be reformed to better account for what happens to the individuals during their working years, but this does not preclude having an equitable health system during childhood. Fourth, people will have different lifespans and they will often not coincide with their life expectancy. This does not mean that differentiating the retirement

[1] Using career length allows to account for the fact that people do not start their working period at the same age due to differences in length of education (see e.g. Schokkaert et al., 2020).

age is a policy that should be abandoned *per se*. But this shows that the benefits obtained from it are not as large as often assumed by those who advocate it. A pension system with a unique career length complemented by *i)* a health or educational policy addressing childhood inequalities and *ii)* better designed and enforced health and safety regulations may be a better option than creating various retirement ages. Designing safer, more adequate and sustainable pension systems is only possible if heterogeneity is taken into account, but implementing this idea turns out to be quite challenging.

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