The Limited Power of Socioeconomic Status to Predict Lifespan: Implications for Pension Policy

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Abstract

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 paper 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 analyze 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.

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Pension policy, Pension progressivity, Lifespan, Tagging
JEL: H55, J14, J18

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. Chetty et al., 2016; Olshansky et al., 2012). This issue has recently received critical attention for its impact on the pension system (OECD, 2018). 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) suggested that the German pension becomes regressive. In order to overcome this problem, the (usual) policy recommendation from the empirical literature has been to differentiate retirement age by socioeconomic status (see e.g. Ayuso et al., 2017). The theoretical literature has reached similar conclusions (see e.g. Leroux et al.,

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2015, for a survey). However, those policies do not take into account the heterogeneity of lifespans 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 paper stresses the importance of also considering lifespan differences.

The difference between life expectancy and lifespan is a key point of this paper. 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 a 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 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 policymakers. They showed that the social planner established a common lower retirement age for short-lived individuals (whatever their occupations) in the first best solution.[1] Then, they discussed the optimal second-best and compared two options: a common social security policy across occupations and tagging (i.e. differentiated retirement age by occupation). They concluded 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 policymakers. 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 missclassified. Short-lived individuals could be tagged as long-lived, because they are mixed in a group with long-lived individuals. This missclassification arises because the decision maker uses observable characteristics (e.g. job) to infer unobservable ones (e.g. lifespan). Using terms introduced

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

by Phelps (1972), the decision maker discriminates "statistically" against short-lived people working in soft occupations.

Drawing from this literature, this paper investigates empirically the importance for pension policy of lifespans 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 lifespans distribution both within and across socioeconomic status for the United States, using mortality rate data assembled by Chetty et al. (2016).

- 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.[2] Under perfect information (i.e. first best), the social planner would chose a different retirement age for each individual based on his lifespan ("individualized retirement age"). However, this is not realistic because it requires to know, 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 individualised 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 paper 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).

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

However, the current pension crisis[3] 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) showed 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 paper 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 *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 identify 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^{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 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 paper, we leave aside those discussions and concentrate on the intrinsic *relevance* of tagging.

A final remark is that our paper 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

[3]Pension systems need to be reformed in many developed economies, essentially due to the growing economic dependency ratio.

[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).

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 differentiation). However, the results would converge. We have chosen to base our paper 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 paper proceeds as follows. Section 2 constructs and presents our "gap index" aimed at measuring the relevance of the socioeconomic tag(s) that could be used by a social planer. Section 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 4. Section 5 details our results. In Section 6, we discuss more in-depth some normative principles underpinning the paper (ex ante vs ex post approach to lifespan and individual vs. group differentiation) and then, we conclude.

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 member (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 member 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

[6] The formal equivalence between retirement age and replacement rate differentiation is developed in Section 3.

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 proposed (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:

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

$$s.t. \quad \mu\left(\mathbf{m}\right) \in \underset{\mu(\mathbf{m})}{\arg\min} \sum_{j=1}^{k} \sum_{i=1}^{n_j} |\delta\left(m_{i,j}\right) - \mu\left(\mathbf{m}\right)|^{\beta} \tag{2}$$

$$\mu_j\left(\mathbf{m_j}\right) \in \underset{\mu_j(\mathbf{m_j})}{\arg\min} \sum_{i=1}^{n_j} |\delta\left(m_{i,j}\right) - \mu_j\left(\mathbf{m_j}\right)|^{\beta}, \forall j \tag{3}$$

The index is the sum, over each individual, of the absolute value of gaps between the individualised 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 (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) ensures that the differentiated retirement ages are those minimizing the sum of the gaps for each of the different retirement ages.[7]

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

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

$$I(\mathbf{m}) = \frac{\sum_{j=1}^{k}\sum_{i=1}^{n_j} |\alpha\, m_{i,j} - \alpha\, \mu_j(\mathbf{m_j})|^{\beta}}{\sum_{j=1}^{k}\sum_{i=1}^{n_j} |\alpha\, m_{i,j} - \alpha\, \mu(\mathbf{m})|^{\beta}} \tag{4}$$

$$s.t. \qquad \mu(\mathbf{m}) \in \arg\min_{\mu(\mathbf{m})} \sum_{j=1}^{k}\sum_{i=1}^{n_j} |\alpha\, m_{i,j} - \alpha\, \mu(\mathbf{m})|^{\beta} \tag{5}$$

$$\mu_j(\mathbf{m_j}) \in \arg\min_{\mu_j(\mathbf{m_j})} \sum_{i=1}^{n_j} |\alpha\, m_{i,j} - \alpha\, \mu_j(\mathbf{m_j})|^{\beta}, \forall j \tag{6}$$

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 Appendix A) 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. Gap index and traditional pension policy

Pension economists might be surprised by the main specification of $\delta(m_{i,j})$ used in this paper (a proportional retirement age). We will argue that there are more connections with the traditional pension policy used in pension economics than it seems.

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 the problem of equalising the ratio of the lifetime pension benefits to the lifetime pension contributions (i.e. equalising the pension rates of returns). This is the very definition of *actuarial fairness* in pensions. Abstracting from the issue of education length differences, career breaks, or demographic changes the rate of returns writes:

$$rr_{i,j} = \frac{m_{i,j} - ra_{i,j}}{ra_{i,j}} \times \mu_{i,j} \tag{7}$$

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

$$rr_{i,j} = \frac{1 - \alpha_{i,j}}{\alpha_{i,j}} \times \mu_{i,j} \tag{8}$$

Imagine, in addition, that we are in a Bismarckian pension system where benefits are strictly proportional to contributions (i.e. $\mu_{i,j} = \mu$), then equalizing rates of returns (achieving actuarial fairness) inevitably requires: $\alpha_{i,j} = \alpha$, $\forall j \forall i$.

One may object that the rate of returns should not be equal whatever the length of life. As such, a higher rate of returns could compensate individuals for a shorter life. In such a case, α should be lower for short-lived individuals. We will provide a robustness check of our result for this statement (see Section 5.5) and shows that our results are not modified by it.

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 Appendix B 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 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 accords 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 stylised 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 amongst the lower socioeconomic status (see e.g. van Raalte et al., 2011).

5. Results

In this section, we report our results and analyze 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 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 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.

5.1. Impact of gap aversion ($\beta \to 10$)

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 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 analyze 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 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 of the 25^{th} percentile and the one of the 75^{th} percentile). This stylized fact is noticeable in the comparison between

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

Figure 2 and 3. Whereas Figure 2 displays a spread of $\alpha \times 4$ years across the different retirement ages by US State, Figure 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 (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 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 5 shows that the distribution characterising the lifespan of men belonging to the 25^{th} income percentile is more dispersed that 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). By 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.

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 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$^{\text{th}}$ and the 51-100$^{\text{th}}$ income percentiles; three brackets that it differs for people in the 1-33$^{\text{th}}$, 34-66$^{\text{th}}$ and the 67-100$^{\text{th}}$ income percentiles. . .

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 (4) as follows:

$$I(\mathbf{m}) = \frac{\left(\sum_{j=1}^{k}\sum_{i=1}^{n_j} |\alpha m_{i,j} - \alpha\mu_j(\mathbf{m_j})|^{\beta} \mid m_{i,j} \leq \mu_j(\mathbf{m_j})\right) + \left(\sum_{j=1}^{k}\sum_{i=1}^{n_j} \sigma|\alpha m_{i,j} - \alpha\mu_j(\mathbf{m_j})|^{\beta} \mid m_{i,j} \geq \mu_j(\mathbf{m_j})\right)}{\left(\sum_{j=1}^{k}\sum_{i=1}^{n_j} |\alpha m_{i,j} - \alpha\mu(\mathbf{m})|^{\beta} \mid m_{i,j} \leq \mu(\mathbf{m})\right) + \left(\sum_{j=1}^{k}\sum_{i=1}^{n_j} \sigma|\alpha m_{i,j} - \alpha\mu(\mathbf{m})|^{\beta} \mid m_{i,j} \geq \mu(\mathbf{m})\right)} \tag{9}$$

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) weight more than the gaps for those who retire too late. Table 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 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.

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 5 shows the computation of the index with different levels of truncation. Remember 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 6) because the planner stops considering the fate of most short-lived individuals. But the values of our gap index remain relatively unaltered.

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 7 shows those two specifications and Table 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 weighting 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 to differentiate the age of retirement across socioeconomic status, they should not underrate the importance of unaccounted lifespan heterogeneity. By focusing only on life expectancy differences (i.e. 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 paper reminds us that there are 4 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, a 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 these 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

[10]For a discussion of the level of job arduousness across sectors and occupation, see Baurin and Hindriks (2019); Baurin et al. (2021).

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.

6. Discussion

In the preceding sections, we have presented our results without discussing *in extenso* some of the normative principles underpinning our paper. 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.

6.1. *Ex post or ex ante equality?*

An *ex ante* framework assesses situation 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 starting argument 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).

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. He wants to differentiate the retirement age because of differences in life expectancy. Starting from a situation with a unique retirement age, he introduces a first differentiation, for example by average lifetime income. However, there is no justification why a social planner should only consider income if he wants to be egalitarian. He should then, for example, further differentiate the retirement age according to the lifetime income of the parents (as we know that childhood circumstances 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 to further differentiation. The social planner's agenda will only be fulfilled when all factors influencing lifespan have been taken into account. However, at that moment, assuming full and perfect knowledge of the whole set of factors affecting lifespan, our social planner will end up with an individualized retirement age, corresponding to the true lifespan of the individual.[11]

Therefore, starting from the point of a social planner who wanted to differentiate the retirement age based on differences of life expectancy, we end up at the point of using differences of lifespans. Fleurbaey et al. (2016, p. 201) already stated that point, slightly differently: "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. In a deterministic world, the true *ex ante* perspective coincides with the *ex post* perspective". 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.

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 paper concentrates 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 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 policymakers 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).

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) argued that differences in health across groups are more informative than differences across individuals because the former removes the component due to luck. This is true. Differences in average health between socioeconomic status show social health inequalities. But, the question is to

[11] Fishkin (2014) used a similar argumentation when he explained the problem of achieving equality of opportunity. He argued 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 slightly difference (e.g. in some genes). The same argumentation applies in our case. The social planner has to take into account every characteristics affecting lifespan if he wants to be egalitarian.

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) showed in his seminal work that a decision maker, with time constraints, could based 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.

7. Conclusion

The pension literature has established that the mortality differential between socioeconomic groups reduces or completely eliminates the progressivity of pension system. To address this problem, 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 paper, we show that differentiating the retirement age by socioeconomic status still leaves a large share of the total heterogeneity of lifespan unaccounted for. Moreover, lifespan distributions across socioeconomic status overlap each others. We have analyzed many different 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 policy).

The take-home message is that pension policy is relatively limited in its capacity to optimally differentiate the retirement age. At individual level, many factors are causing enormous variation 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. This paper 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 emphasized that health policy should directly target sick people, rather than income groups.

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. 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 lifespans 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).[12]

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Declarations of interest

None

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

Data and code availability

All data and code necessary for replication of the results are freely available at https://github.com/sirarno93/The-Limited-Power-of-Socioeconomic-Status-to-Predict-Lifespan. The author remains available for all requests concerning the data and their treatments. The original mortality rates of Chetty et al. (2016) can be downloaded from https://healthinequality.org/data/.

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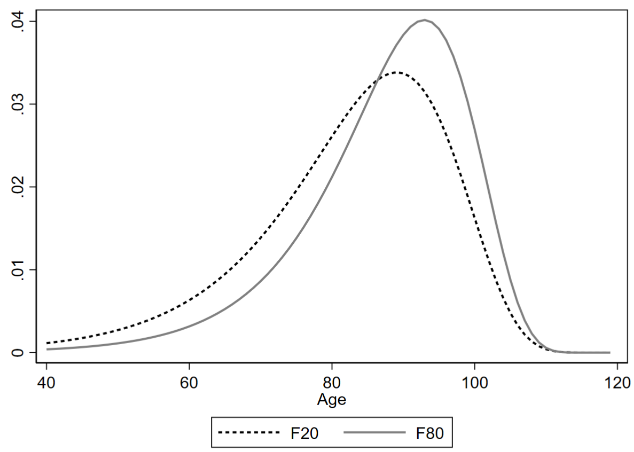
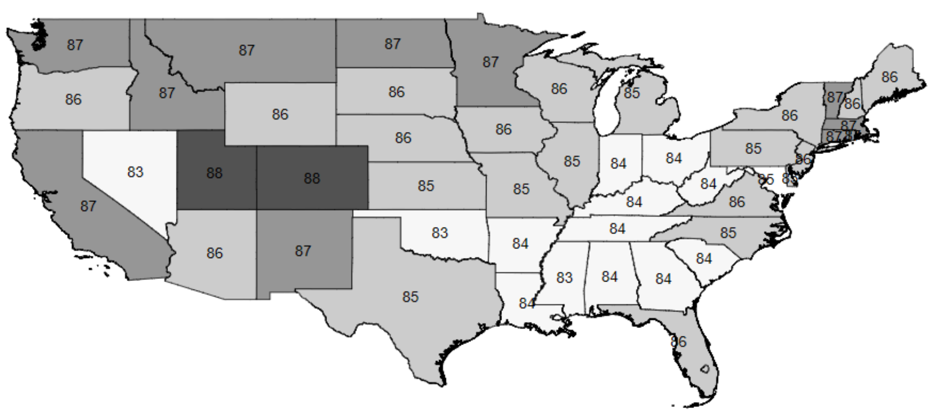


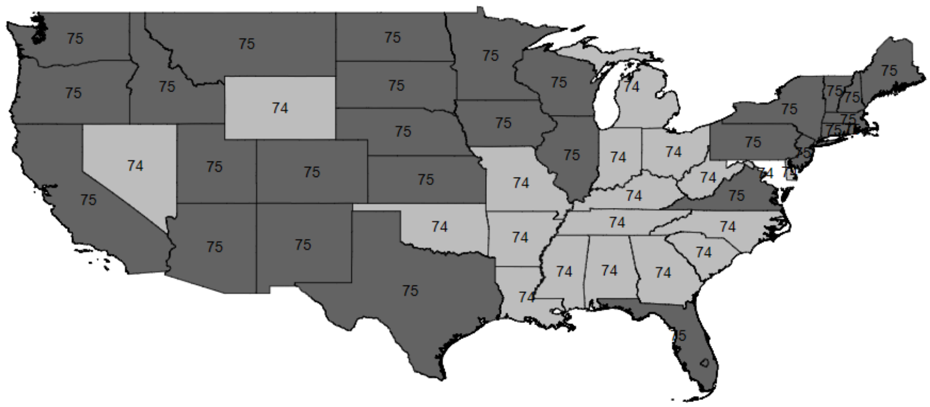
The figure shows the simulation of US lifespan distribution for women in the 20$^{\text{th}}$ and 80$^{\text{th}}$ income percentile. Simulations are done using the mortality rates provided by Chetty et al. (2016). The lifespan distribution of the women with a higher income is more negatively skewed 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 1: Distribution of lifespan for women in the 20$^{\text{th}}$ and the 80$^{\text{th}}$ percentile



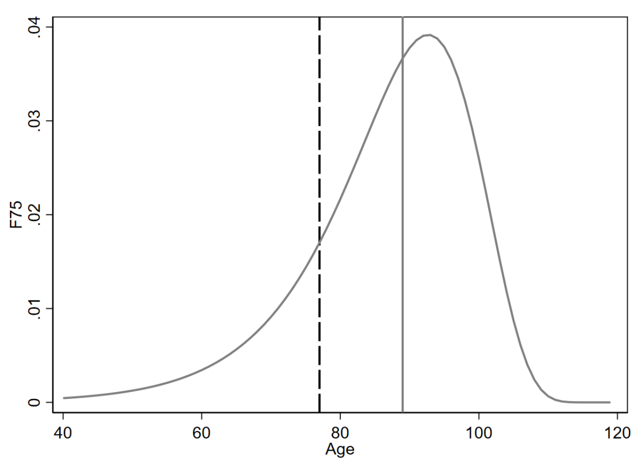
The figure shows the retirement age by state of residence with β and α equal to 1. Simulations use the mortality rates provided by Chetty et al. (2016) .

Figure 2: Impact of differentiating the retirement age by state (β and $\alpha = 1$)



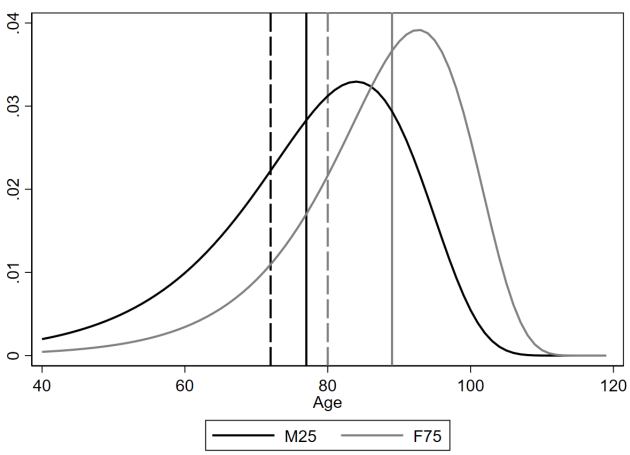
The figure shows the retirement age by state of residence with β equal to 10 (and α equal to 1). Simulations use the mortality rates provided by Chetty et al. (2016) .

Figure 3: Impact of differentiating the retirement age by state ($\beta = 10$, $\alpha = 1$)



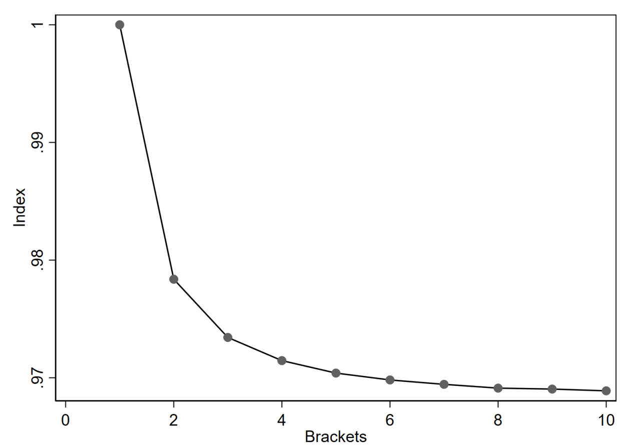
The figure shows the decrease in the retirement age when β increases. Simulations use the mortality rates provided by Chetty et al. (2016). The retirement age (with α equal to 1) is the solid line when β equal 1 and the dashed one when β equal 10.

Figure 4: Explanation of the decrease of the retirement age (Women, 75^{th} percentile)



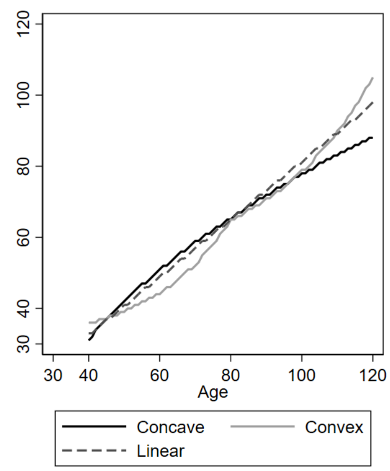
The figure shows the decrease in the spread between the retirement ages when β increases. Simulations are done using the mortality rates provided by Chetty et al. (2016). The retirement age for the men in the 25^{th} income percentile (with α equal to 1) is the solid black line when β equal 1 and the 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 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 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 follow: $\delta\left(m_{i,j}\right) = -10+10*\sqrt{m_{i,j}-23}$. The second is linear (i.e. proportional) and is obtained as follow: $\delta\left(m_{i,j}\right) = 81.25\,\% \times m_{i,j}$. The third is convex and is obtained as follow: $\delta\left(m_{i,j}\right) = e^{m_{i,j}/22.5}+30$ 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 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 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 2: Index and retirement age for various value 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: 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 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 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 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 7: Index and retirement age for several policies ($\beta = 1$)

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

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 $\mu(\mathbf{m})$:

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

The derivative of (A.1) with respect to $\mu(\mathbf{m})$ is:

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

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

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

Condition (A.3) 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 (A.3) and the social planner finds the root by computation and by applying condition (A.3). For an even value of β, the root is located at the following condition:

$$\sum_{i=1}^{n} (\alpha m_i - \alpha\mu(\mathbf{m}))^{\beta-1} = 0 \tag{A.4}$$

Condition (A.4) states that μ is the mean when β equals 2. There exists no statistical name to the condition (A.4) when β is even and above 2 and the social planner finds the root by computation and by applying condition (A.4).

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)[13] which they computed based on a sample of

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

1,4 billion observations from anonymised tax records between 1999 and 2014. Their mortality rates are the empirical one 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 B.1 shows the lifespan distribution for women in the 20^{th} and in the 80^{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^{th} percentile because there are more person alive at 91 in it than in the 20^{th} and the change to the NCHS-SSA mortality rate is therefore more reflected in it.

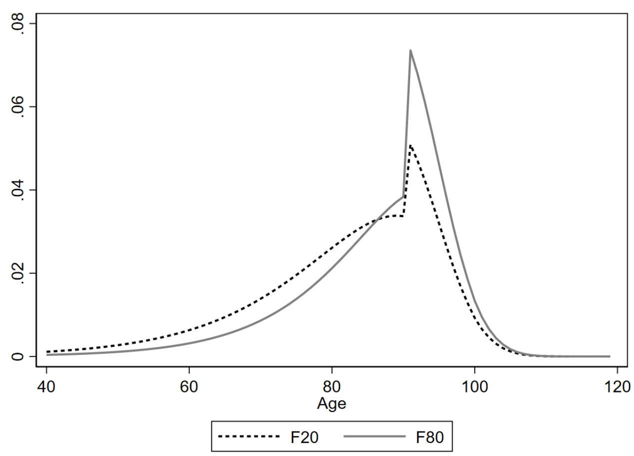


Figure B.1: Distribution of lifespan for women in the 20^{th} and the 80^{th} percentile

The presence of this spike could raises 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) found 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.[14] As there is not much individuals living older than 105, extending the Gompertz curve until the end is not a strong assumption. In the main part of the paper, we use graphs based on the Gompertz curve for reading easiness (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

[14]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.

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,[15] 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

Appendix C.1. Index and retirement age for various value 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 C.1: Index and retirement age for various values of β

Appendix C.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 C.2: Retirement age by σ (β and $\alpha = 1$)

[15] 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).

Appendix C.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 C.3: Index by σ and by β

Appendix C.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 C.4: Index with different levels of truncation ($\beta = 1$)

Appendix C.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 C.5: Retirement ages with different levels of truncation (β and $\alpha = 1$)

Appendix C.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