The Measure of Population Aging in Different Welfare Regimes: A Bayesian Dynamic Modeling Approach

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Abstract

Given a population at a specific time point, it is often of interest to identify the entry age into typical stages of life, such as being young, becoming adult and elderly. These age cutoffs are important because they influence the public opinion and have an impact on policy decisions. An issue of great social relevance is defining the threshold beyond which a person becomes elderly. Fixed cutoffs are debatable because of their conventional nature which disregards issues such as changing life expectancy and the evolving structure of the age distribution. The above shortcomings can be overcome if age cutoffs are defined *endogenously*, i.e., relative to the whole age distribution of each country at a specific time point. We pursue this line of research by presenting an analysis whose main features are: (1) establishing a relationship between a country's *welfare regime* and its age distribution and aging process, together with the identification of four clusters of countries corresponding to distinctive welfare models and (2) a Bayesian hierarchical dynamic model which accounts for the uncertainty in the time series of measurements of the endogenous cutoffs for the countries in the sample, as well as for their clustering structure. Our analysis leads to *model-based* estimates of country-specific endogenous age cutoffs and corresponding aging indicators. Additionally, we provide *cluster-specific* estimates, a novel contribution engendered by the use of hierarchical modeling, which widens the scope of our analysis beyond the countries which are present in the sample.

Keywords Age cutoff · Aging indicator · Bayesian hierarchical dynamic model · Kullback–Leibler divergence · Longevity · Welfare regime

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1 Introduction

Population aging is a global phenomenon with profound implications in many domains of human life, see Lutz et al. (2008), Christensen et al. (2009) and European Commission (2014). It is considered one of the greatest social and economic challenges of the twenty-first century. If people aged 60 years or over are classified as “elderly”, then according to recent population prospects United Nations (2013), their number is expected to increase from 841 million people in 2013 to more than 2 billion in 2050. Measures of the entry age into various stages of life (e.g., young, adult, elderly), as well as aging indicators, are important because they influence the public opinion and have an impact on policy makers. In the public debate, there is still not sufficient awareness of the fact that the magnitude and speed of population aging are strictly dependent on the definition of “elderly people”. Thanks to the improvement in longevity, health conditions and lifestyle, it is hard to regard similarly an individual aged 60 years today or in 1950, let alone in the year 2050.

Conventional thresholds (such as 60 or 65 years of age) to define elderly people are often related to eligibility criteria for admissions to social or welfare programs in various countries. Methods to determine thresholds are rapidly changing, and also the use of fixed thresholds seems to be debatable, see, for example, Sanderson and Scherbov (2010), Shoven (2010), d’Albis and Collard (2013), Demuru and Egidi (2016) and Bordone et al. (2016).

The aging process is in general merely treated as an issue of variation in the number of elderly people in a population; but it is also, and more importantly, a question of variation of the age at entry in the elderly status, and more generally a question of redefining the boundaries of the different stages of life. This issue has been extensively debated although nonconclusive results have been reached; see Sanderson and Scherbov (2010), Shoven (2010) and Roebuck (1979). As a consequence, the usual indicators based on fixed thresholds (traditionally 60 or 65 years) are still employed in official statistics, as well as in international comparative reports.

In the scientific literature, two main approaches may be found on the issue of how to measure dynamically population aging. The first focuses on the impact of longevity on the life course. The seminal contribution for this approach is the paper of Ryder (1975) wherein it is proposed to define old people as those above the age corresponding to a remaining life expectancy of 10 (or 15) years; see also, among others, Sanderson and Scherbov (2008). The second adopts a population-level perspective and takes into account the modification on the age profiles produced not only by the mortality decline but also by other demographic determinants of population dynamics, and in particular by the evolution of fertility; see for instance Chu (1997) and Nath and Islam (2009).

Recently, d’Albis and Collard (2013) have suggested an interesting method to determine optimal age groupings in a population. The characterizing feature of their proposal is that age cutoffs, which determine the groupings, are defined *endogenously*, i.e., relative to the actual age distribution of each country in the

given year. Importantly, the whole shape of the age distribution is taken into account (and not only some summary measures) so that information loss is minimal. Using this approach, they found that over the last 50 years, an important aging indicator, such as the elder-child ratio, has increased between 6.5% in the USA and an average of 8% in the industrialized countries. These findings suggest that aging is less pronounced, when fixed conventional thresholds are substituted with measures that take into account the evolution of the entire age distribution.

It should also be considered that population aging takes place jointly with changes in society and shifts at the level of individual life courses (better lifestyle, advances in technology, educational expansion, delayed entry into the labor market, flexibilization and increasing uncertainties in life and professional career, growing regional mobility, postponement of full autonomy and family formation), Komp and Johansson (2015). These transformations tend to produce a combined impact on the age when full independence from parents is achieved, on the length of the transition process to adulthood, on family ties and cross-generational relationships [see Vogel et al. (2017) which also relates the transition process to adulthood with the different welfare regimes].

Welfare regimes are a crucial factor to understand the evolution of age distributions and more specifically the phenomenon of aging (see Aysan and Beaujot 2009; Vogel 2009; Myles 1984; Natali and Rodhes 2004).

Welfare is the provision of services and financial support for the protection and promotion of the physical and material well-being of citizens. The welfare system can vary in the different countries in relation to the different role of the government, the market, the families and reflect the mix of cultural peculiarities and institutional specificities.

The welfare state emerged in the late nineteenth century to solve social problems (such as poverty, disability, senescence). Before its development, people were generally working until they were disabled through poor health. Mature modern societies are not characterized by a single welfare model: different regimes are present, depending on the different articulation and responsibilities assumed for social security by the state, the market and the family in the welfare provision. Differences in the welfare mix are due to cultural peculiarities as well as institutional specificities and reflect the balance between intergenerational ties and individualization in the way citizens face social risks in different countries; see Taylor-Gooby (2004) and Ranci (2012).

Causes and implications of demographic changes are strictly interrelated with the welfare system. From one side, the welfare system has an influence on the demographic dynamics and structure through the impact on reproductive choices and on longevity (produced, among others, by the strength of intergenerational family ties, pronatalistic policies, measures for reconciling work and family care, long-term care, health system, promotion of active aging). From the other side, the demographic change (aging in particular) tends to produce an impact in the welfare system and on its sustainability (public and private intergenerational transfers, public pensions, formal and informal long-term health care); see Vogel (2009).

All these aspects lead to a reconsideration of roles, functions and opportunities during all the life courses. The entry age into typical stages of life is therefore

challenged with the consequent impact on social policies and how people organize their life. In particular, the better life conditions for older age-groups have enhanced a steady shift forward of the threshold between adulthood and old age; see Sander-son and Scherbov (2010) and Schwanitz et al. (2017).

Retirement is certainly a key milestone in individual life but it corresponds less and less to a net discontinuity between a "before" and "after." In addition, such a phase tends to become a flexible boundary, which can be anticipated or delayed within an increasingly wider age range, and it varies among generations based on the longer average life expectancy. Nevertheless, the access to benefits and social services is usually based on static age limits. The state pension age is one important example. But it is also true that several European countries are discussing reforms to adopt a dynamic scheme to the pension age (linked to the evolution of life expectancy); see, for example, Vogel et al. (2017).

The aim of our paper is to elaborate on the notion of age cutoffs, defined endogenously, in order to gain a deeper understanding of the dynamics of the age distribution in the industrialized countries. We pursue this line of research by presenting an analysis whose main features are: (1) establishing a relationship between a country's *welfare regime* and its age distribution and aging process, together with the identification of four clusters of countries corresponding to distinctive welfare models and (2) a Bayesian hierarchical dynamic model which accounts for the uncertainty in the time series of measurements of the endogenous cutoffs for the countries in the sample, as well as for their clustering structure.

The results of our analysis will be an analytical description of the evolution in time of the *countries-specific* age cutoffs for each cluster and of the dynamics of the underlying *cluster-specific* cutoffs, an aggregate estimate of cutoffs producing an overall aging trend for each cluster. Additionally, the estimated country-specific cutoffs can be used to elaborate *aging indicators* that will be compared between countries and between clusters.

We emphasize that the novelty of our work rests on the application of hierarchical modeling in the context of age-related indicators. From a substantive point of view, this paper provides an original contribution to the debate in the scientific literature on how to overcome the static thresholds of entry into old age, adopting in particular the population-level approach. This allows to assess how much the share of the elderly in the population and the ratio between the elderly and the young become less burdensome once the age cutoffs are defined endogenously, so that the evolution of the whole age distribution is taken into account. The cutoffs obtained by the population-level approach are influenced not only by variations in longevity but also by other demographic and social transformations which, in the different welfare systems, act on the juvenile, adult and elderly condition. In addition, in terms of policy implications, this approach directly links the costs of pensions, public health care and resources devoted to caregiving to the modification on the age profiles and, specifically, to the number of people dynamically attributed to the elderly category. At the basis of this approach lies the idea that the definition of the age of entry into the old age-group, on the one hand, and the political choices related to the age of access to various social services and the corresponding costs, on the other, are features which are increasingly becoming less static and more interdependent.

The paper is organized as follows. Section 2 first summarizes the method developed by d'Albis and Collard (2013) to compute the empirical age cutoffs and illustrates their time evolution, and then discusses welfare regimes in relation to the proposed clustering structure and describes our Bayesian hierarchical dynamic linear model and its concrete implementation. In Sect. 3, we present model-based estimates of age cutoffs and aging indicators at both the country and cluster levels. Finally, Sect. 4 considers a few issues for discussion. To ease the flow of exposition, some plots and tables were placed in the Web-based supporting material.

2 Data and Methods

2.1 Empirical Age Cutoffs

The dataset of the Human Mortality Database (www.mortality.org) contains the time series of the age distributions of the population, from birth to age 110, for male and female separately or total (both sexes). They are available for 39 industrialized countries over a period that approximately spans the second half of the twentieth century until 2014. Each age distribution is represented by a highly detailed histogram with 111 classes, each bin having width of 1 year.

d'Albis and Collard (2013) proposed a methodology to construct, separately for each country and year, a much coarser histogram having a very small number of classes. (In their paper, they considered four age classes, broadly representing the four stages of life: child, young, adult/mature and old.) The three age cutoffs, which identify the four classes, represent an important source of demographic information; of particular interest is the first cutoff (the lower threshold for being considered a young person), and the third cutoff (the threshold over which a person is considered to be elderly). Their method rests on previous theoretical work by Aghevli and Mehran (1981) who discussed a histogram *approximation* to a continuous distribution using the Lorenz concentration function. The key idea introduced in the latter paper was to define the approximation error in terms of two Gini's absolute pairwise differences: one defined on the original continuous distribution and the other evaluated under the histogram. For a given number of bins, Aghevli and Mehran (1981) define the *optimal* histogram as that which minimizes the approximation error. From a geometric perspective, the optimal histogram minimizes the area between the Lorenz curve computed under the continuous distribution and that computed under the approximating histogram.

In the setup considered by d'Albis and Collard (2013), the starting distribution is a highly detailed histogram with over 100 classes, while the resulting histogram is a four-class histogram. They were able to identify the optimal cutoff points of the coarse histogram by means of a recursive system of equations. They also provided further theoretical insights that help appreciate their methodology; in particular, they showed that their method is invariant with respect to proportional rescaling of distributions.

They used data for both sexes combined of a sample of 14 countries, namely Australia, Austria, Canada, Denmark, France, Iceland, Italy, the Netherlands, Norway,

Spain, Sweden, Switzerland, UK, USA starting from 1751 (Sweden) to 1947 (Austria) and ending from 2003 (Italy and UK) to 2005.

The age cutoffs computed for each year on each of the 14 industrialized countries are then used to construct endogenous, country-specific, aging indicators. Of particular interest is the share of the elderly people in the total population, and the elder–child ratio, which is computed as the ratio of the share of the elderly people over that of the people classified as children (age up to the first cutoff).

In this paper, we use as data the time series of the three optimal age cutoffs presented in d’Albis and Collard (2013), for each year and country. (Data and their matlab code are available from the personal Web page of d’Albis, <http://www.hdalbis.com>, at the link of Research Publications.)

We call these cutoffs *empirical* in order to distinguish them from the *parametric* cutoffs that will be derived using our model-based approach. For comparative purposes, we consider the time series of the three empirical age cutoffs from 1947 to 2003, because for this time interval data are available for all 14 countries. The plots of all these time series are reported in Fig. 1 of the Web-based supporting materials. Despite the heterogeneity of these data (an issue that will be addressed in the subsequent sections), we briefly summarize their main features for the sake of the reader.

Broadly speaking, each of the three age cutoffs has increased over time in all countries. In particular, the first cutoff, which defines the entry age for the young people, starts around age 14–18 in 1947 and reaches the age bracket 18–24 in 2003. The increasing trend of the first cutoff is particularly pronounced in some countries where, in the 1960s, the effect of the postwar baby boom is more evident. The evolution of the second cutoff, which determines the lower bound for the class of adult people, starts around 30–35 years of age and can reach values somewhat between 35 and 42 in the year 2003, after presenting a slight drop in the late 1960s. Of great interest is the evolution of the third age cutoff which marks the entry age in the class of elderly people. This threshold was around 50–54 in the late 1940s and has increased to values in the interval 55–62 by the year 2003.

2.2 Clusters of Welfare Regimes

Although all 14 countries in the sample are broadly labeled as “industrial”, there exists prior socio-demographic knowledge that allows to split them into more homogeneous groups relative to the focus of our analysis. Several criteria may be adopted in identifying groups of relatively homogeneous countries with regard to age distribution, and in particular aging indicators. Our choice is based on subject matter considerations and relates substantive demographic features of a country to its underlying *welfare regime*. Other options are, however, possible and consistent with the methodology proposed in this paper for the subsequent statistical analysis.

We decided to adopt a classification consistent with Esping-Andersen’s proposal (Esping-Andersen 1990), with the addition of the Southern European “model”. The 14 countries in our study were accordingly clustered as shown in Table 1.

In his seminal paper (Esping-Andersen 1990), see also Esping-Andersen (1999), he proposed a threefold taxonomy of welfare regimes. A social democratic model

Table 1 Cluster structure of the 14 industrialized countries based on welfare regimes

Cluster 1	Denmark–Iceland–Norway–Sweden
Cluster 2	Australia–Canada–Switzerland UK–USA
Cluster 3	Austria–France–The Netherlands
Cluster 4	Italy–Spain

(dominating in Scandinavia) exhibiting a strong degree of individualization and a prominent role of the state: the welfare system is financed by high taxes and individuals have equal access to public services; a conservative model (prominent in Continental Europe) with less egalitarianism/universalism and a more corporatist/paternalistic approach than the social democratic model: social security is mainly financed by contributions and is markedly stratified by gender and occupation; and a liberal model (such as the UK and Ireland in Europe and the USA and Canada outside Europe) where individual initiative and the role of the market are considered more important: state provision is limited and restricted to social assistance. The papers by Esping-Andersen have stimulated a rich debate over the last 25 years, both at the conceptual and empirical level; see, among others, Castles and Mitchell (1993), Pitruzzello (1999), Pierson (2000) and Powell and Barrientos (2004). His categorization of countries has been widely used in the scientific literature with some proposals of adjustments, ranging from how to classify “hybrid cases” to the addition of a fourth model. In particular, several authors have stressed the importance to recognize the distinctive anthropological and institutional characteristics of the Southern European (or Mediterranean) “social model” (Jurado Guerrero and Naldini 1996a, b; Trifiletti 1999; Arts and Gelissen 2002; Ranci 2012), including countries such as Italy, Spain and Greece. This suggests the identification of a fourth cluster of countries combining strong family ties and informal help with strong gender and generational segmentation and high levels of social inequality.

2.3 A Bayesian Hierarchical Dynamic Model for the Estimation of Age Cutoffs

Consider a given empirical cutoff y_{it} (e.g., the third one) for country i at time t . The key idea is that y_{it} is a measurement, subject to error, of a *underlying* cutoff θ_{it} . To see why this standpoint is appropriate, simply observe that the cutoff y_{it} produced by the method of d’Albis and Collard (2013) is the result of a procedure which best approximates, relative to a specific optimization criterion, a highly detailed histogram with one having only four classes. Alternative criteria will inevitably lead to different values; yet they all try to measure the same quantity θ_{it} . As a consequence, our primary goal becomes the estimation of θ_{it} , which in turn requires the specification of a suitable statistical model relating the data y_{it} to the parameter θ_{it} .

We take advantage of the similarity of countries within each cluster by means of a Bayesian hierarchical model which allows to share information across countries; see Gelman et al. (2014) for a detailed exposition of the rewards of hierarchical

modeling. This in turn benefits the estimation procedure of *country-specific* parameters, because it is based on a larger basis of related information; see comments after formula (1). Additionally, and importantly, we are able to provide estimates of *cluster-specific* parameters, which represent a salient feature of our approach.

Consider the time series $\{y_{it}; i \in C, t = 1, \dots, T\}$ of empirical cutoffs for the subset of countries belonging to cluster C . Because of their assumed similarity, we model the collective observations $\{y_{it}; i \in C, t = 1, \dots, T\}$ jointly using a hierarchical dynamic linear model (HDLM); see, for instance, Petris et al. (2009). While the dynamic nature of the model accounts for dependence across time, the appealing feature of the hierarchical component is that the estimate of the country-specific cutoff θ_{it} will depend not only on the data for country i , but also on the data of the other countries in the cluster, thus exploiting more fully the information available. For a general account of hierarchical modeling, we refer the reader to Gelman and Hill (2007), while the more specialized topic of HDLM is discussed in Petris et al. (2009).

Assume that the size of the set C is m . Then, our HDLM is described by the following three equations ($i \in C, t = 1, \dots, T$)

$$\begin{aligned} y_{it} &= \theta_{it} + \epsilon_{i1t}, & \epsilon_{1t} &\sim \mathcal{N}_m(0, V_y) \\ \theta_{it} &= \lambda_t + \epsilon_{i2t}, & \epsilon_{2t} &\sim \mathcal{N}_m(0, V_\theta) \\ \lambda_t &= \lambda_{t-1} + \epsilon_{3t}, & \epsilon_{3t} &\sim \mathcal{N}(0, \sigma_\lambda^2), \end{aligned} \quad (1)$$

where $\epsilon_{1t} = (\epsilon_{i1t}, i \in C)$, and similarly for ϵ_{2t} , while $\mathcal{N}_m(a, B)$ denotes the m -dimensional normal distribution with mean a and variance-covariance matrix B (when $m = 1$ it is omitted from the notation). Furthermore, the error components ϵ_{lt} ($l = 1, 2, 3$) are assumed to be jointly independent.

The first equation is a standard measurement error model relating observations to their corresponding parameters. The second equation of model (1) treats the vector of *country-specific cutoffs* ($\theta_{it}, i \in C$)'s as originating from the distribution $\mathcal{N}_m(\lambda_t \mathbf{1}_m, V_\theta)$, where $\mathbf{1}_m$ is the unit vector of length m . The common mean λ_t may be regarded as the underlying *cluster-specific cutoff* and reflects the assumption that countries in the same cluster share some broad similarities. Finally, the third equation describes the evolution of λ_t over time. For simplicity, we decided to model it as a simple random walk, a standard basic stochastic process which appears to be suited to the actual time evolution. Alternative dynamic features, which may include a trend for instance, could be easily incorporated, however.

Because of the assumed homogeneity of countries within each cluster, we specified a simple structure for the covariance matrices, namely $V_y = \sigma_y^2 I_m$ and $V_\theta = \sigma_\theta^2 I_m$, where I_m is the identity matrix of order m . The latter assumption in particular amounts to treating the country-specific cutoffs θ_{it} as *exchangeable* because, conditionally on λ_t and σ_θ^2 , they represent independent and identically distributed draws from the same distribution $\mathcal{N}(\lambda_t, \sigma_\theta^2)$.

To complete the model specification, weakly informative independent inverse-gamma priors were assigned to the variance components σ_y^2 , σ_θ^2 and σ_λ^2 . In our application, we set the expectation equal to 1 and the variance equal to 1000. We

also performed some sensitivity analysis on these values and found no appreciable differences in our results.

Estimation and forecasting are solved by computing the conditional distributions of the quantities of interest, given the available information. To carry out full inference on the model, we will have to estimate first of all the variance components. Bayesian inference about them must be based on their posterior distribution; this distribution is generally not analytically tractable, and then we have to simulate from it. Markov chain Monte Carlo (MCMC) methods are the numerical methods used to come up with posterior summaries: a sample of the variance components is drawn from their full conditional distributions, and the parameter estimation is done through convenient summaries; see Petris et al. (2009, Sects 4.5–4.6).

An important feature of dynamic models is the ability of the prospective assessment in addition to the retrospective assessment given by its online inferential procedure. This means that at any time point the sequential analysis can be stopped to allow for parametric estimation of the system at the same time or at the previous time given all the available information. These procedures are called filtering or smoothing as they filter back the information smoothly via a recursive algorithm.

In the filtering problem, we want to compute the conditional density of the country-specific cutoffs $p(\theta_{is}|y_{i1}, \dots, y_{it})$ with $s = t$, while in the smoothing problem we want to compute the conditional density $p(\theta_{is}|y_{i1}, \dots, y_{it})$ with $s < t$. These calculations can be performed using again a hybrid version of MCMC method. Specifically, to draw from the full conditionals of the θ_{it} , $t = 1, \dots, T$, one can use the forward filtering backward sampling (FFBS) method (Carter and Kohn 1994; Frühwirth-Schnatter 1994) that provides a recursion method for computing the mean and variance of the posterior distribution of θ_{it} , $t = 1, \dots, T$, conditionally on the data.

Computations in our HDLM were performed using the R package *dlm* by Petris (2010). We found that 10000 iterations of the MCMC algorithm, in addition to 1000 as burn-in, were typically sufficient to achieve convergence and good mixing properties of the MCMC sampler, as assessed by trace plots and conventional summary diagnostics.

2.4 Kullback–Leibler Divergence

To answer the question “How well separated are the cluster cutoffs?” we will use the classic Kullback–Leibler (*KL*) divergence.

Let P and Q be two probability measures, each admitting density, p and q , respectively, relative to some dominating measure, which we assume for simplicity to be Lebesgue measure. The *KL* divergence of q from p , written $KL(p||q)$, is defined as $KL(p||q) = \int p(x) \log(q(x)/p(x)) dx$. *KL* is nonnegative and takes the value zero if and only if P and Q are equal almost everywhere. *KL* is not symmetric, a feature which is undesirable in our case given that we regard clusters on an equal footing. One can, however, symmetrize it by taking the Kullback–Leibler symmetrized (*KLS*) divergence:

$$KLS(p, q) = KL(p||q) + KL(q||p).$$

(Other options are clearly available.) Trivially, $KLS(pq)$ is nonnegative, and the value zero characterizes equality of the two measures (almost everywhere).

It is well known that there is no upper bound for KL , and hence for KLS . This makes it somewhat difficult to interpret its values. To enhance our understanding, we can calibrate KL divergence in a simple way.

Suppose that $KL(p||q) = k$, $k \geq 0$. To assess the strength of this discrepancy, McCulloch (1989) suggested the following strategy: let $KL(Ber(0.5)||Ber(q))$ denote the KL divergence of a Bernoulli variate with success probability q from a Bernoulli (0.5) (the fair coin tossing setup).

If $q = q(k)$ is such that

$$KL(Ber(0.5)||Ber(q(k))) = k,$$

then $q(k)$ represents an effective calibration of the value $KL(p||q) = k$. For instance, suppose $q(k) = 0.55$, then the divergence $KL(p||q) = k$ is very small, because it corresponds to that between the fair coin tossing scenario and a Bernoulli trial with success probability only slightly higher (0.55). Conversely, if $q(k) = 0.9$, then $KL(p||q) = k$ is actually very strong. Clearly, the existence of a unique $q(k)$ requires $KL(Ber(0.5)||Ber(q))$ to be invertible as a function of q ; this can be achieved by requiring $0.5 \leq q \leq 1$ because in this case $KL(Ber(0.5)||Ber(q))$ is increasing in q . Additionally, if k is a value larger than $\max_{0.5 \leq q \leq 1} KL(Ber(0.5)||Ber(q))$, then a sensible calibration would be to set $q(k) = 1$.

3 Results

3.1 Age Cutoffs

3.1.1 Country-Specific Cutoffs

In this subsection, we examine the evolution of the estimated age cutoffs in the four clusters characterizing the distinct welfare regimes, resulting from our model. In particular, we present plots of the various estimates of country-specific cutoffs over the whole period 1947–2003. We complement the above plots with more detailed information and display tables containing the expectation and standard deviation of the smoothing distribution of country-specific cutoffs for selected years, separately for each cluster and each age cutoff.

To streamline exposition, we discuss widely in the main text of the paper the results for the estimated third country-specific cutoffs (the most interesting one in a demographic context), and in a more synthetic way the results for the first country-specific cutoffs (since we will use them to define the aging indicators). However, plots and tables for the estimated first and second country-specific cutoffs are displayed in the Web-based supporting material (see Figs. 2, 3 and Tables 1, 2).

Figure 1 reports, for each cluster, the evolution of the country-specific third cutoffs; see also Table 2. It is apparent that the entry age in the elderly group (third cutoff) increases over time within each cluster. Nevertheless, important differences may be identified. In particular, cluster 4 shows the lowest entry age at the beginning of the period (the mid-twentieth century), but also the strongest increase over time,

almost reaching the threshold of 60 years in the first years of this century. In cluster 2, the third cutoff starts at around 52 (2 years higher than in cluster 4), and this value reaches 59 at the end of the period.

As stressed by d'Albis and Collard (2013), the approach leading to endogenous cutoffs makes use of the entire demographic distribution, and therefore it incorporates not only the effect of longevity, but also any change in the shape of the distribution. For instance, the Southern European countries experienced a sharp reduction in the fertility rate in the last decades of the twentieth century with a strong impact on the aging process, which is mirrored in the steep increase of the curve.

Fig. 1 Country-specific third cutoffs, from 1947 to 2003, for each cluster

Table 2 Country-specific third cutoffs by cluster for selected years: expectation and standard deviation (SD) of smoothing distribution

Cluster 1	Year	Denmark	Sweden	Norway	Iceland	
	1947	52.07	52.91	52.55	51.24	
	1957	54.03	54.80	54.34	52.32	
	1967	55.04	55.68	55.29	52.78	
	1977	57.30	58.11	57.61	54.68	
	1987	57.18	58.05	57.32	54.92	
	1997	58.27	59.07	58.19	56.08	
	2003	59.26	60.22	59.12	57.03	
	SD	1.2460	1.2422	1.2415	1.2413	
Cluster 2	Year	Switzerland	UK	Canada	USA	Australia
	1947	52.29	53.05	51.01	51.63	51.80
	1957	53.75	54.69	51.64	52.77	52.52
	1967	53.76	54.83	51.96	53.22	52.62
	1977	55.79	56.59	53.55	54.73	53.86
	1987	56.41	56.63	54.43	55.06	54.39
	1997	57.90	58.14	56.28	56.44	56.18
	2003	58.91	59.01	57.37	57.20	57.44
	SD	1.0966	1.0821	1.0803	1.0801	1.0800

Table 2 (continued)

Cluster 3	Year	France	Austria	Netherland
	1947	53.42	52.89	52.37
	1957	56.08	56.25	53.69
	1967	54.94	55.76	53.91
	1977	56.78	57.55	55.73
	1987	56.84	57.09	55.95
	1997	58.15	58.55	57.59
	2003	59.35	59.31	58.64
	SD	0.8579	0.8557	0.8554
Cluster 4	Year	Italy	Spain	
	1947	49.98	49.68	
	1957	52.61	51.79	
	1967	53.45	52.55	
	1977	55.65	54.90	
	1987	57.38	56.77	
	1997	59.81	59.08	
	2003	61.07	59.98	
	SD	0.7861	0.7827	

It is also interesting to observe that, within each cluster, some countries show noticeable deviations from the pattern exhibited by fellow countries. This, in particular, is the case of Iceland in cluster 1, which presents uniformly lower values of the third cutoff, and the Netherlands which emerge as a hybrid case (see also Kammer et al. 2012) in cluster 3, showing an appreciable deviation from the remaining countries at the beginning of the time period under investigation together with a convergent pattern as time progresses. A fair degree of heterogeneity is present in cluster 2, which may be in part attributable to the coexistence of countries from different continents.

To further appreciate the evolution of country-specific third cutoffs, Table 2 reports, for each cluster, the expectation of the smoothing distribution for selected years. (The last line contains the standard deviation which is not reported for each individual year because its value is highly stable over time.)

As we previously said, we will use the first cutoff in the aging indicators (e.g., share of the youngest), so it is interesting to observe its evolution over time. In Fig. 2 of the Web-based supporting material, we can see that the evolution of the country-specific first cutoffs is increasing for each cluster. In the first cluster, Iceland presents uniformly lower values among the other fellow countries and presents the minimum entry age at the beginning of the period. On the other hand, in cluster 4, Italy presents the maximum first cutoff (around to 24) at the end of the period. In cluster 3, the Netherlands again emerges as a hybrid case as its evolution starts with very low values but ends with high values (over 20).

3.1.2 Cluster-Specific Cutoffs

A distinctive feature of our hierarchical dynamic linear model (1) is represented by the parameter λ_t , namely the mean cutoff of the cluster at time t . The dynamic evolution of this parameter provides useful information which goes beyond that of the individual countries because it tries to summarize an aggregate behavior for all countries sharing a specific welfare regime (also beyond those included in the sample).

With reference to the third cutoff, Fig. 2 displays the evolution of the four cluster-specific parameters, while Table 3 contains the posterior expectation and standard deviation of the smoothed distribution for selected years. It is interesting to remark

Fig. 2 Cluster-specific third cutoffs from 1947 to 2003, based on the four welfare regimes

Table 3 Cluster-specific third cutoffs for selected years: expectation and standard deviation of smoothing distribution

Year	Cluster 1	Cluster 2	Cluster 3	Cluster 4
1947	52.32	52.03	52.70	50.11
1957	53.94	53.07	55.43	52.31
1967	54.94	53.43	54.95	53.16
1977	57.09	55.02	56.76	55.44
1987	56.89	55.49	56.69	57.31
1997	58.08	57.18	58.32	59.67
2003	58.84	57.94	59.07	60.48
SD	0.7389	0.6370	0.6346	0.6687

that cluster 4 (Southern European), although not included in the original classification proposed by Esping-Andersen (1990), exhibits the steepest increase in the entry age into the elderly group; indeed, its value rises from around 50 in 1947 and reaches 60.5 years in 2003. The behaviors for cluster 1 (Scandinavian countries) and cluster 3 (Continental Europe) are very similar, especially from the 1970s onward. At the beginning of the period, the cutoff is around 52.5, and then it rises, following a non-uniform trend, up to 59. Both these values are slightly higher in cluster 3. Finally, the behavior of cluster 2 (which includes North America, Australia, UK and Switzerland) exhibits the smallest growth: the cutoff increases less than 6 years throughout the period. Moreover, it is also the cluster that presents systematically lower values of entry age into the elderly group from 1977 onward.

Table 5 in the Web-based supporting materials contains the posterior expectation of the variance components of model (1) together with their MCMC standard errors. In particular, they provide an estimate of within-cluster variability for the individual observations (σ_v^2) together with an estimate of cluster variability for the mean (σ_θ^2). One can see that the within-cluster variability is pretty similar across clusters.

We now consider in some detail the issue of separation of the cluster cutoffs. For the sake of clarity, and with a slight modification of the notation used in model (1), let λ_{ct} denote a cluster-specific age cutoff at time t for cluster c . (The following argument is valid for any of the three cutoffs, so we could consider any of them; for definiteness, however, we shall refer to the third one.)

Recall that λ_{ct} is a random variable whose uncertainty can be represented through its smoothing distribution, which is approximately normal because the smoothing distribution is computed for each t in retrospect using all the available data. We validated this claim through an analysis of the MCMC draws both graphically and through formal tests. Using the summary values in Table 3, one could in principle compute an approximate credibility interval (say at 95% level) in the usual way, extending the expected value on either side by two standard deviations to obtain the lower and upper end points of the interval. A quick inspection of the values in Table 3 reveals that, for each t , these intervals will typically overlap across clusters. While the extent of the overlapping depends on the time period, one can broadly conclude it will be substantial between clusters 1 and 3 and only moderate between cluster 4 and any of the other three clusters, emphasizing the peculiar behavior of

the Southern European group with regard to the remaining clusters. While credibility intervals are a useful way to convey uncertainty about parametric inference, their overlapping across groups does not imply that the underlying distributions are not well separated.

We addressed this issue using the *KLS* divergence. Specifically, we computed, for all $t = 1, \dots, T$, and each distinct pair of clusters $\{c, c'\}$ ($c \neq c'$),

$$KLS(p^S(\lambda_{c_t}), p^S(\lambda_{c'_t})) = k_t(c, c'),$$

where $p^S(\cdot)$ stands for the smoothed distribution. To summarize all these individual divergences, we calculated the median $k(c, c') = \text{median}_{\{t=1, \dots, T\}} \{k_t(c, c')\}$; finally, $k(c, c')$ was calibrated with the value $q(k(c, c'))$ as described above. The result of this exercise, relative to the third age cutoff, is reported in Table 4.

Save for the pair 1–3, to which we return shortly below, all divergences calibrate to Bernoulli probability exceeding 0.99. This means that our clustering structure is capturing substantial differences in terms of the entry age into the elderly class. In particular, the highest value is reported for the pair 1–4, closely followed by the pair 2–3. The smallest divergence (0.29) is reported for the pair of clusters 1–3 which translates to a calibrated probability of 0.72. While not overwhelming as in the previous pairwise comparisons, this value can be regarded as an appreciable distinction from the benchmark probability 0.5. Our findings show that the clusters suggested by the literature on welfare regimes are useful to identify differences in the intensity and dynamics of the aging process between countries. Indeed, the age structure in a population is mostly influenced by the dynamics of birth rate and the increase in life expectancy, which in turn are linked to a variety of social and structural factors depending on the welfare mix. These factors have contributed to a great extent in shifting forward the entry age into the elderly class. This effect is most noticeable for the Southern European countries (an increase of 10 years from 1947 to 2003). On the other hand, countries belonging to the liberal model (cluster 2) have experienced a comparatively smaller variation, while the social democratic model (cluster 1) and Continental Europe (cluster 3) occupy an intermediate position, as our results show. When comparing the latter two clusters, one can see that the Continental European group presents a higher third cutoff at the beginning of the period and a stronger increase in the last decades (from 1987 to 2003 an increase below 2 years in cluster 1 while for cluster 3 the corresponding value is 2.3).

The same analysis could be done for the other two cluster-specific age cutoffs, but, as in the previous section, here we highlight some details only for the first cutoff. In Fig. 4 (first panel) of the Web-based supporting material, we can analyze the evolution of the cluster-specific first cutoffs for each cluster. It is interesting to see

Table 4 Third cutoff. Symmetrized Kullback–Leibler divergence $k(c, c')$ and corresponding calibration value $q(k(c, c'))$ for all pairs of cluster-specific cutoffs

Pairs of clusters	1–2	1–3	1–4	2–3	2–4	3–4
$k(c, c')$	3.19	0.29	5.28	5.10	2.54	4.52
$q(k(c, c'))$	0.99	0.72	0.9999	0.9999	0.99	0.999

again that cluster 4 exhibits the steepest increase in the entry age into the youngest group; indeed, its value rises from around 15 years in 1947 and 23 in 2003.

The behaviors for cluster 2 and cluster 3 are exactly the same even if the values of cluster 2 are always lower than ones of cluster 3. Starting from the same value of 16 years in 1947, their evolution is very similar until 2003 where their values are around 20 (for cluster 2) and 21 (for cluster 3).

Finally, the behavior of cluster 1 exhibits the smallest growth: the cutoff increases less than 5 years throughout the period, from 16 years in 1947 to 20 years in the end of the period.

3.2 Aging Indicators

Population aging takes place jointly with changes in society and shifts at the level of individual life courses as already highlighted in Introduction. These transformations tend to produce a combined impact not only on retirement on the age when full independence from parents is achieved, on the length of the transition process to adulthood, on family ties and cross-generational relationships.

To better appreciate the dynamics of aging, we considered three aging indicators: (1) the share of the youngest, i.e., the proportion of people in the first age-group (up to the first cutoff); (2) the share of the elderly, i.e., the proportion of people above the third cutoff; (3) the elder-child ratio, namely the share of the oldest divided by the share of the youngest. We recall that these indicators have the appealing property of being invariant to any proportional rescaling of the age distribution, following an increase in life expectancy (d'Albis and Collard 2013, Appendix 6).

Figure 3 shows the evolution over time of the three aging indicators for each cluster, while Table 5 reports some of their values for selected years with their means and standard deviations from 1947 to 2003.

In general, it appears that the share of the youngest is generally higher than the share of elderly. In fact, the range for the average values of the share of youngest is from 27.78% (for cluster 1) to 29.04% (for cluster 2) while for the averages of the share of elderly is from 20.08% (for cluster 2) to 22.62% (for cluster 1).

With regard to the share of the youngest for each cluster, a remarkable fluctuation around its mean does not appear because of the low values of the standard deviations, between 0.011 and 0.015.

Cluster 2 starts off in the 1950s and 1960s with the highest share which is above 0.3; subsequently, this value declines until the 1990s and finally picks up again in the last years so that this indicator is still the highest in the last years. A relative stability is exhibited by cluster 3 with values hovering around 0.28 with some decline in the 1990s and finishing second in the early years of 2000. Cluster 1, which comprises the Scandinavian countries, is consistently below the remaining clusters (except for the very last years) with values somewhat higher than 0.25 until the 1990s and then somewhat below this line. Finally, the Southern European countries exhibit the sharpest decline starting in the late 1980s, and finishing with the smallest value around 0.23 in the year 2003.

We remark that the share of youngest is mainly affected by the fertility dynamics and in particular by the baby boom, and the subsequent slowdown which was especially marked in Southern Europe.

We now turn to analyzing the share of the elderly which, once allowing for time-varying age cutoffs, does not grow; an exception is represented by the Southern European group whose share of the elderly grows, although far less rapidly than the usual aging indicator based on a fixed threshold (typically 60 or 65 years). In particular, the share of the elderly remains relatively more stable for all the clusters as we can see from the very low values of the standard deviations (all less than 0.010).

With regard to this last cluster, the value rose from around 0.19 at the beginning of the period to nearly 0.22 in the final years.

Fig. 3 Aging indicators from 1947 to 2003 for each cluster

Table 5 Aging indicators for selected years for each cluster with their means and standard deviations from 1947 to 2003

Year	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Share of the youngest				
1947	0.26	0.28	0.26	0.27
1957	0.28	0.30	0.28	0.29
1967	0.26	0.31	0.27	0.27
1977	0.26	0.30	0.28	0.28
1987	0.24	0.27	0.28	0.27
1997	0.25	0.28	0.27	0.25
2003	0.25	0.29	0.27	0.23
Mean	0.2579	0.2904	0.2789	0.2738
SD	0.012	0.014	0.011	0.015
Share of the elderly				
1947	0.21	0.20	0.21	0.19
1957	0.22	0.21	0.20	0.19
1967	0.23	0.20	0.22	0.21
1977	0.23	0.21	0.20	0.20
1987	0.24	0.21	0.21	0.21
1997	0.22	0.19	0.21	0.22
2003	0.22	0.19	0.21	0.22
Mean	0.2262	0.2008	0.2111	0.2083
SD	0.009	0.006	0.006	0.010
Elder-child ratio				
1947	0.81	0.71	0.82	0.70
1957	0.80	0.68	0.72	0.67
1967	0.88	0.67	0.80	0.78
1977	0.90	0.70	0.69	0.70
1987	0.99	0.77	0.77	0.79
1997	0.88	0.67	0.78	0.90
2003	0.90	0.67	0.78	0.96
Mean	0.8794	0.6934	0.7581	0.7648
SD	0.062	0.041	0.039	0.078

The greatest stability over the years is exhibited by cluster 3, followed by clusters 1 and 2, so that one may conclude that the populations in these clusters have not aged over the years. With regard to the aging process, the elder-child ratio is of particular interest. Clearly, cluster 3 exhibits the most stable evolution. The strongest variation over time, on the contrary, can be observed for cluster 4. There are also remarkable differences among clusters. In particular, while in cluster 4 the share of elderly almost reaches that of the youngest, in cluster 2 it remains around 30% lower.

4 Discussion

Population aging is one of the greatest challenges of this century. Measures of this process are important because they influence the public opinion and have an impact on policy decision.

In general, social conditions influence life courses: on the other hand, changes in life courses have an impact on demographic patterns of a country. In aging countries, we can observe a general shift in focus from government-based and/or family-based care, to more diversified care systems (with more private and market-based options).

An increase in public awareness is also important, since these changes challenge the nature of politics where the time horizon is the next election, not someone's life span. Maintaining a static and stereotyped view can be dangerous in an aging society with continuously changing individual paths (see Komp and Johansson 2015 or Lee and Goldstein 2003).

Unlike endogenous mechanisms, exogenous thresholds require continuous renegotiation for their adaptation. In general, the fact that so far access to various services and benefits is defined exogenously is not a good reason to believe that it should always remain so. In a dynamic world facing unparalleled age transformation, do we have only to replicate old static schemes or should we try to experiment new solutions?

Individuals welcome longer life, but for populations, increases in this magnitude could impose heavy costs on the working age-groups and could have other substantial but uncertain economic and social consequences. These consequences will depend in large part on how the additional expected years of life are distributed across the various social and economic stages of the life cycle.

There is a general consensus that the aging process cannot be adequately addressed by simply tracing the proportion of people exceeding a conventional age threshold (usually 60 or 65) over time. On the other hand, endogenous age cutoffs, which take into account the whole structure of the age distribution, appear as more sensible measures of entry points into the stages of life (youngest, young, adult, elderly).

The dynamics of the demographic process are not the same across countries and are strictly connected with the anthropological and structural aspects of the welfare regimes. For example, developed countries are all aging but at different paces and levels. The cultural and institutional responses are also different. In particular, Aysan and Beaujot (2009) show that there is no single path to pension reform: "While there are some variations, welfare states tend to follow their traditional paths, which differ across welfare regime types". Pensions and health services are a relevant part of the welfare policies.

The classification of industrialized countries according to welfare regimes is widely used in demographic and social policy literature. It is therefore particularly interesting to test how the various models of welfare regimes differ from one another in terms of the evolution of the age distribution and the corresponding age cutoffs.

We adopted a classification of countries according to three “models” of welfare (social democratic, conservative and liberal) complemented with a fourth one (Southern European) representing a convenient framework for analyzing countries jointly rather than individually.

Specifically, we model each of the three empirical age cutoffs produced by the method of d’Albis and Collard (2013) through a hierarchical dynamic linear model. In this way, we obtain model-based country-specific and cluster-specific estimates of age cutoffs. The latter in particular represent a distinctive contribution of this work, because they attempt to measure the underlying cutoffs specific to the welfare regime corresponding to the various clusters.

In our approach, we preselected clusters of countries based on substantive knowledge about the prevailing welfare regimes across industrialized countries. We confirmed the validity of this choice by showing a strong or very strong separation between all pairs of cluster cutoffs, as measured by the symmetrized Kullback–Leibler divergence.

Other options are, however, available and consistent with the methodology proposed in this paper; for instance, clusters of countries could be obtained by performing a cluster analysis.

Moreover, in principle, one could dispense with exogenous prior information and model the data of all countries simultaneously with the double aim of discovering a clustering structure and estimating country and cluster parameters of interest. We expect that this line of research would require a more elaborate modeling framework than the one used in this paper, but could lead to interesting results for comparison purposes.

In our analysis, we used a simple HDLM; in particular, we have modeled the country-specific cutoffs θ_{it} ’s as exchangeable, while the cluster cutoffs λ_t ’s are modeled through a random walk. Elaborations of this model can be envisaged, for instance, by building a regression structure for the evolution of the θ_{it} ’s, whenever relevant covariates are available, or by postulating a more complex time-evolving paths for the λ_t ’s including, for instance, a time trend. These modifications would add flexibility to our model and could be easily accommodated in terms of implementation.

Our method takes as input the age cutoffs of the total population, for both sexes combined, constructed according to the method proposed by d’Albis and Collard (2013). The latter postulates a fixed number of age-groups, and this naturally raises the issue of robustness of the ensuing aging indicators. Their findings, however, are reassuring: while the level of the shares of the age-groups varies with the number of groups, the overall time evolution is quite similar across different number of groups. Accordingly the general conclusion that the evolution of the share of the oldest is much more limited than commonly depicted continues to hold.

Interesting issues to study in the future could be the robustness of our results with respect to the differences between male and female and the updating of the aging indicators based on more recent data.

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Compliance with ethical standards

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References

- Aghevli, B. B., & Mehran, F. (1981). Optimal grouping of income distribution data. *Journal of the American Statistical Association*, 76(373), 22–26.
- Arts, W., & Gelissen, J. (2002). Three worlds of welfare or more? *Journal of European Social Policy*, 12, 137–158.
- Aysan, M. F., & Beaujot, R. (2009). Welfare regimes for aging populations: No single path for reform. *Population and Development Review*, 35, 701–720.
- Bordone, V., Arpino, B., & Rosina, A. (2016). Forever young? prevalence and correlates of feeling old. *ESRC Centre for Population Change - Briefing*, 37, 1–4.
- Carter, C. K., & Kohn, R. (1994). On Gibbs sampling for state space models. *Biometrika*, 81(3), 541–553.
- Castles, F. G., & Mitchell, D. (1993). *Worlds of welfare and families of nations* (pp. 93–128). Aldershot: Dartmouth Publishing Company.
- Christensen, K., Doblhammer, G., Rau, R., & Vaupel, J. (2009). Aging populations: The challenges ahead. *Lancet*, 374, 1196–208.
- Chu, C. Y. C. (1997). Age-distribution dynamics and aging indexes. *Demography*, 34(4), 551–563.
- d’Albis, H., & Collard, F. (2013). Age groups and the measure of population aging. *Demographic Research*, 29(23), 617–640. <https://doi.org/10.4054/DemRes.2013.29.23>.
- Demuru, E., & Egidi, V. (2016). Adjusting prospective old-age thresholds by health status: Empirical findings and implications. A case study of Italy. *Vienna Yearbook of Population Research*, 14, 131–154.
- Esping-Andersen, G. (1990). *The three worlds of welfare capitalism*. London: Polity.
- Esping-Andersen, G. (1999). *Social foundations of post-industrial economies*. Oxford: Oxford University Press.
- European Commission. (2014). *Population ageing in Europe. Facts, implications and policies*. Luxembourg: Publications Office of the European Union.
- Frühwirth-Schnatter, S. (1994). Data augmentation and dynamic linear models. *Journal of Time Series Analysis*, 15(2), 183–202.
- Gelman, A., & Hill, J. (2007). *Data analysis using regression and multilevel/hierarchical models*. Cambridge: Cambridge University Press.
- Gelman, A., Carlin, J. B., Stern, H. S., Dunson, D. B., Vehtari, A., & Rubin, D. B. (2014). *Bayesian data analysis* (3rd ed.). Texts in Statistical Science Series Boca Raton, FL: CRC Press.
- Jurado Guerrero, T., & Naldini, M. (1996a). Is the south so different? Italian and Spanish families in comparative perspective. *South European Society & Politics*, 1, 42–66.
- Jurado Guerrero, T., & Naldini, M. (1996b). The southern model of welfare in social Europe. *Journal of European Social Policy*, 6, 17–37.
- Kammer, A., Niehues, J., & Peichl, A. (2012). Welfare state regime and welfare state outcomes in Europe. *Journal of European Social Policy*, 22, 453–469.
- Komp, K., & Johansson, S. (Eds.). (2015). *Population Ageing from a Lifecourse Perspective*. Critical and International Approaches Chicago: The University of Chicago Press.
- Lee, R., & Goldstein, J. R. (2003). Rescaling the life cycle: Longevity and proportionality. *Population and Development Review*, 29, 183–207.
- Lutz, W., Sanderson, W., & Scherbov, S. (2008). The coming acceleration of global population ageing. *Nature*, 451, 716–719.
- McCulloch, R. E. (1989). Local model influence. *Journal of the American Statistical Association*, 84(406), 473–478.
- Myles, J. (1984). *Old age in the welfare state*. Boston: Little Brown - Business & Economics.

- Natali, D., & Rodhes, M. (2004). The new politics of the bismarckian welfare state: Pension reforms in continental europe. *EUI Working Paper* vol. 10, pp. 1–32
- Nath, D., & Islam, M. (2009). New indices: An application of measuring the aging process of some Asian countries with special reference to Bangladesh. *Journal of Population Ageing*, 2(1–2), 23–39.
- Petris, G. (2010). An R package for dynamic linear models. *Journal of Statistical Software*, 36(12), 1–16.
- Petris, G., Petrone, S., & Campagnoli, P. (2009). *Dynamic linear models with R. Use R!*. New York: Springer.
- Pierson, C. (2000). Three worlds of welfare state research. *Comparative Political Studies*, 33, 791–821.
- Pitruzzello, S. (1999). *Decommodification and the worlds of welfare capitalism: A cluster analysis*. Florence: European University Institute.
- Powell, M., & Barrientos, A. (2004). Welfare regimes and the welfare mix. *European Journal of Political Research*, 43, 83–105.
- Ranci, C. (2012). *Social vulnerability in Europe the new configuration of social risks*. Basingstoke: Palgrave Macmillan.
- Roebuck, J. (1979). When does “old age begin?: The evolution of the english definition. *Journal of Social History*, 12(3), 416–428.
- Ryder, N. B. (1975). Notes on stationary populations. *Population Index*, 41(1), 3–28.
- Sanderson, W., & Scherbov, S. (2008). Rethinking age and ageing. *Population Bulletin*, 63, 1–17.
- Sanderson, W. C., & Scherbov, S. (2010). Remeasuring aging. *Science*, 329(5997), 1287–1288.
- Schwanitz, K., Mulder, C., & Toulemon, L. (2017). Differences in leaving home by individual and parental education among young adults in europe. *Demographic Research*, 37, 1975–2010.
- Shoven, J. B. (2010). New age thinking: Alternative ways of measuring age, their relationship to labor force participation, government policies, and gdp. In D. A. Wise (Ed.), *Research findings in the economics of aging* (pp. 17–31). Chicago: University of Chicago Press.
- Taylor-Gooby, P. (2004). *New risks. New welfare. The trasformation of the European welfare state*. Oxford: Oxford University Press.
- Trifiletti, R. (1999). Southern European welfare regimes and the worsening position of women. *Journal of European Social Policy*, 9, 49–64.
- United Nations. (2013). *World population ageing 2013*. New York: Department of Economic & Social Affairs.
- Vogel, J. (2009). The European welfare mix: Institutional configuration and distributive outcome in Sweden and the European Union. A longitudinal and comparative perspective. *Social Indicators Research*, 48, 245–297.
- Vogel, E., Ludwig, A., & Börsch-Supan, A. (2017). Aging and pension reform: Extending the retirement age and human capital formation. *Journal of Pension Economics and Finance*, 16(1), 81.

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