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DEPENDENCY EVOLUTION IN SPANISH DISABLED POPULATION: A FUNCTIONAL DATA ANALYSIS APPROACH

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Abstract

In a health context dependency is defined as lack of autonomy in performing basic activities of daily living that require the care of another person or significant help. However, this contingency, if present, changes throughout the lifetime. In fact, empirical evidence shows that, once this situation occurs, it is almost impossible to return to the previous state and in most cases the intensity increases. In this article, the evolution of the intensity in this situation is studied for the Spanish population affected by this contingency. Evolution in dependency can be seen as sparsely observed functional data, where for each individual we get a curve only observed at those points in which changes in the condition of his/her dependency occur. We use functional data analysis techniques such as curve registration, functional data depth or distance-based clustering to analyse this kind of data. This approach proves to be useful in this context since it takes into account the dynamics of the dependency process and provides more meaningful conclusions than simple pointwise or multivariate analysis. The database analysed comes from the Survey about Disabilities, Personal Autonomy and Dependency Situations, EDAD 2008, (Spanish National Institute of Statistics, 2008). The evaluation of the dependency situation for each person is ruled in Spain by the Royal Decree 504/2007 that passes the scale for assessment of the situation set by Act 39/2006. In this article, the scale value for each individual included in EDAD 2008 has been calculated according to this legislation. Differences between sex, ages and first appearance time have been considered and prediction of future evolution of dependency is obtained.

Keywords: Chain-ladder; dependency; disability; forecasting; functional data; time warping model.

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1 Introduction

When we refer to normal living, we usually imagine a situation in which people can do all things that they need or wish to do on a daily basis such as dressing, feeding, drinking or bathing independently. Unfortunately, this is not always possible because of the presence of a disability. This turns into a tougher situation if another person is required to help complete all of these activities. In this case, we would be talking about dependency. Traditionally this problem has been treated as a question of health. However, since the beginning of this century, social aspects of this problem are also considered (WHO (2001)). In fact, the The International Classification of Functioning, Disability and Health (ICF) tries to establish a consensus in its understanding, by establishing a difference between the basic activities of daily life and the instrumental activities of daily life ($BADL$ and $IADL$, respectively). The ADLs are the basic tasks of everyday life. BADLs consist of self-care tasks, including personal hygiene, dressing, feeding, functional transfers, etc. A useful mnemonic is $DEATH$: dressing, eating, ambulating, toileting, hygiene. IADLs are not necessary for fundamental functioning, but they let an individual live independently in a community (Bookman *et al.* (2007)). These tasks include cooking, cleaning, shopping, healthcare and medication, using telephones and technology, caring for other individuals and pets, etc.

There are many ways to define what *dependency* is. One of the most accepted is that included in Resolution R(98) of the Council of Europe that defines it as "such state in which people, whom for reason connected to the lack or loss of physical, mental or intellectual autonomy, require assistance and/or extensive help in order to carry out common everyday actions".

Despite this general definition, the real situation is that every country has translated it to their national legislations in an heterogeneous way (Kamette (2011)). Although surprising, it can be possible that a man/woman can be considered as a dependent person in a country but not in another. Let us look at an example. According to French legislation, a person can only be considered dependent if he/she is over 60 years old. So, a 45 year old individual can not be classified as dependent in France, regardless of his/her health condition, but could be in Spain or in Germany (see Albarrán, Alonso, and Bolancé (2009)). Focusing on Spain, the definition of dependency is that included in article 2 of Act 39/2006, of 14^{th} December, on the Promotion, Personal Autonomy and care for Dependent persons. It is defined as a "permanent state in which persons that for reasons derived from age, illness or disability and linked to the lack or loss of physical, mental, intellectual or sensorial autonomy require the care of another person/other people or significant help in order to perform basic activities of daily living or, in the case of people with mental disabilities or illness, other support for personal autonomy".

Not all dependents are suffering this contingency with the same intensity. So, one of the main issues is the measurement of dependency. Usually, a scale is used to do it. The most standard item to evaluate is the time another person dedicates to helping a dependent do certain activities such as dressing or feeding themselves. This is the assessment used by the German or Spanish systems. For instance, the Spanish scale is ruled by the Royal Decree 504/2007, of 20^{th} April, that passes the scale for assessment of the situations of dependency set by Act 39/2006. According to it, the scale goes from 0 to 100 points and at least 25 points are needed to acknowledge entitlement to the benefits of the system.

There is another aspect related to dependency that can not be forgotten, which is the increase in intensity throughout the lifetime. As one can assume, dependency generally increases in intensity with age. This article tries to analyse the evolution of this suffering throughout the lifetime once it has been diagnosed. We are particularly interested in predicting future dependency scores at the final years of a person's life. Then we consider dependency as a continuous process. In order to reflect the way the intensity of this contingency changes along time, a time warping model has been used to analyse the data. The statistical information used in this study was collected by the Disabilities, Personal Autonomy and Dependency Situations Survey, known as EDAD, according to its Spanish acronym. This recent macro-survey on dependency was conducted through a collaboration agreement between the Spanish National Institute of Statistics (INE), the State Department for Social Services, Family and Disability Support (via the Office of Coordination of Sectorial Policies for the Disabled and the Institute for Older People and Social Services IMSERSO) and the ONCE Foundation (the Spanish Organization for the Blind). The aim of the survey is to obtain the most relevant information available about the situation of dependent persons. It is adapted to current social situations and is guided by the philosophy of the International Classification of Functioning, Disability and Health published by the World Health Organization. Data were collected in 2008. In the first wave of the survey, more than 260,000 people living in private households were interviewed. In a second wave, more than 11,000 people living in public or private residencies were also included.

The rest of the article is organized as follows. In Section 2 we describe the survey EDAD 2008 and present our data. We also introduce the time warping model used to analyse the data and different procedures to estimate a "mean" evolution curve and to identify different profiles among individuals. Finally, we describe a method to predict future dependency scores from the estimations. Section 3 includes the analysis of the data coming from EDAD 2008 according to the methodology presented in Section 2, as well as the projected score values with their confidence bands. Finally, Section 4 is devoted to discuss the results.

2 Methods

The most recent large-scale, nation-wide household survey developed in Spain is the 2008 Survey on Disabilities, Independency and Dependency Situations (Encuesta sobre Discapacidades, Autonomía personal y situaciones de Dependencia - EDAD 2008). This is is the largest survey ever performed in Spain.

The survey was conducted in two stages with complementary questionnaires: the first is geared to the respondents' homes and their characteristics, and the second is focused on individuals with an additional questionnaire on disabilities for those aged 6 or above. Nine groups of disabilities were analyzed: sight; hearing; communication; learning, knowledge application and task development; mobility; self-care; domestic life; interpersonal interactions and relationships. To define disability, the survey refers to the International Classification of Functioning, Disability and Health (ICF), produced by the World Health Organization (WHO (2001)), and regards disability as: "*... major restrictions on the performance of daily activities, which have lasted or are expected to last more than one year, and which originate from an impairment*" (INE (2010)). The survey defines impairments as problems affecting the functions of bodily systems (physiological functions) or bodily structures (anatomical parts) and which have led to a restriction of the individual's activity. Hence, this survey is based on the concept of self perceived disability, in accordance with the recommendations of the World Health Organization. So, target individuals are identified through a set of questions about the possible difficulties they can find in doing some specific activities.

In order to provide reliable estimates at the national level, the survey was performed around the country using stratified two-stage sampling (see INE (2010) for more details on the sampling methodology). The survey was prepared interviewing 260,000 people who were living in 96,000 different houses whereas for institutionalized people, 11,000 people in 800 centers were asked about their situation. According to EDAD 2008, there are more than 4.1 million Spaniards suffering at least one kind of disability, 3.85 million out of them living with their relatives or in their own homes, whereas the remaining 0.27 millions are in specialized centers. Indeed, the sampling design provides a weight associated to each individual in the sample indicating how many people in the population he/she represents. Although the global prevalence rate of disability is 9.1%, in the case of people living at home this rate is lower than that for people living in institutions (8.5% and 17.7%, respectively). Disability is mainly related to two main variables: sex and age. Until 45 year old, the male prevalence is greater than the female one. After that age, the relative incidence is greater for women. In general terms, more than 50% of the people suffering at least one kind of disability are at least 65 year old, being most of them women. However, this paper is focused on the analysis of dependency. According to the former definition of dependency, all dependents are disabled but the opposite is not always true. In fact, according to the Spanish system a dependent person is one that reaches a score greater than 0 when being evaluated with the official scale. Also, among dependents, those with a score greater than 25 points are entitled to receive public aids. A detailed explanation about the scale and the scores obtained for this sample can be found in Albarrán and Alonso (2009). The results with EDAD 2008 suggest that more than 1.4 million people can be considered dependent. More than 485,000 of them are men and the remainder 921,000 are women. In Figure 1 we present a summary of the sample in terms of age and sex composition, indicating the estimated population size they represent. We also show mean dependency score values by age and gender. Almost 84.5% of the individuals of the sample are over 50 year old. However, this ratio is quite different between men (73.7 %) and women (88.6 %). In this paper we analyse the evolution of the Spanish dependent population throughout time. Since we are particularly interested in studying dependency in the final years of a person's life, we consider only the dependent population over 50, distinguishing between men and women. The distribution of sex and age of the individuals included in the analysis is shown in Table 1.

In a first step, we aim at performing a descriptive analysis of the dependency trajectories obtained from the database. If we think of the evolution of dependency as a continuous process, we may consider these data as individual realizations of that process, observed only at those moments at which changes in the personal situations occur. Then, methods for analysing sparsely

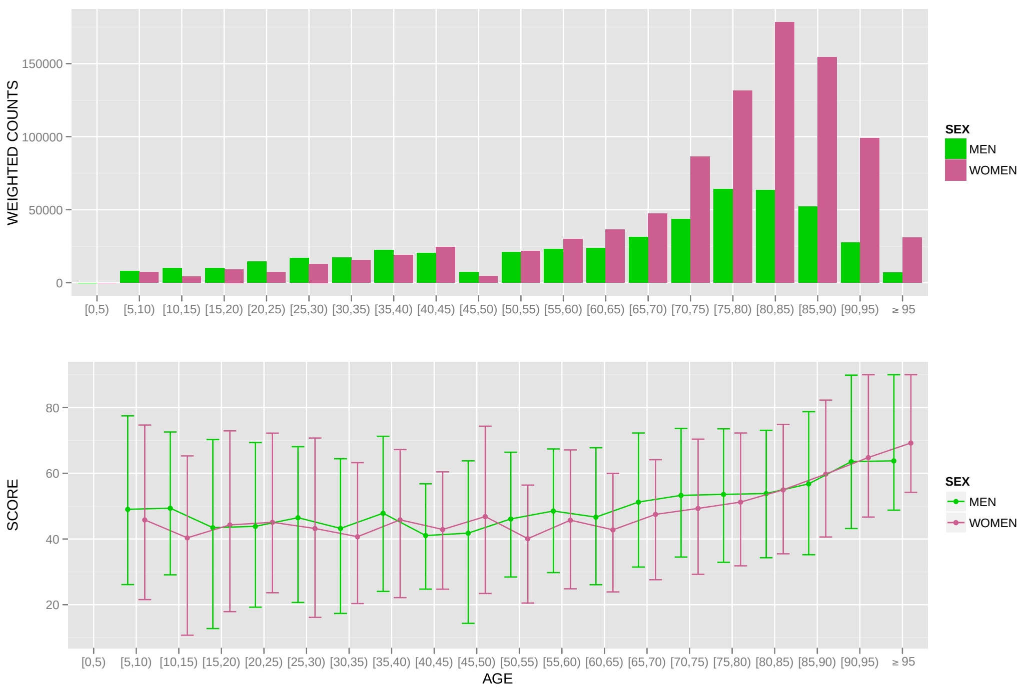

Figure 1: Top: Age distribution in the sample for men (green) and women (purple). Bottom: Mean score with first and third quartile by age for men (green) and women (purple).

Table 1: Dependents classified by age and sex

Group of age	Men		Women	
	Estimated Population Size	Sample Size	Estimated Population Size	Sample Size
$[50, 55)$	20,816	137	21,297	130
$[55, 60)$	22,403	146	29,678	174
$[60, 65)$	23,237	157	35,555	233
$[65, 70)$	29,291	173	44,970	281
$[70, 75)$	41,452	310	82,572	549
$[75, 80)$	62,026	408	125,631	802
$[80, 85)$	60,025	396	168,817	1053
$[85, 90)$	50,271	308	148,157	903
$[90, 95)$	25,330	263	95,168	924
≥ 95	6,171	44	29,702	198
Total	341,021	2342	781,618	5247

Source: own elaboration, EDAD 2008 and RD 505/2007 and irregularly observed functional data are of interest here.

First, let us describe our data as functional observations. The data set consists of individual information containing the ages at which each person in the sample have suffered any alteration in his/her health condition leading to a jump in his or her dependency score, together with his or her current age. Then, for the i-th individual we observe $(t_{i1}, y_{i1}), \ldots, (t_{in_i}, y_{in_i})$, the ages at which changes are produced and the dependency scores at these ages, and a_i, the current age. From these data, in order to stress the step character of these curves, we add a first point $(0, 0)$ (only if $t_{i1} > 0$), intermediate points $(t_{ih} - \delta, y_{ih-1})$ between (t_{ih-1}, y_{ih-1}) and (t_{ih}, y_{ih}), where δ is a chosen short period of time, and a final point (a_i, y_{in_i}) (only if $t_{in_i} < a_i$). These transformed sequences will conform our set of observations from now on. For the sake of simplicity, we will still refer to them as $(t_{ih}, y_{ih})_{h=1,\ldots,n_i}$, $i = 1, \ldots, n$.

Then we have n discretely observed curves $y_1, \ldots, y_n$ defined in different time intervals $[0, a_i]$, $i = 1, \ldots, n$. However, in order to apply any functional data analysis technique, we need functions defined over the same interval. One idea would be to consider the different cohorts present in the sample and to analyse the dependency trajectories within each cohort. However, this may lead to many different under-represented cohorts, since the age range of the individuals in the sample is large. Instead of that we consider disjoint groups of people of ages in intervals of 5 years. Within each interval of age $[A, A + 5)$ we truncate individual curves to get them defined in $[0, A]$. Then, we have the following k groups of individuals and curves

$$\mathcal{I}_A = \{i \,|\, 1 \leq i \leq n,\, a_i \in [A, A+5)\} \qquad \mathcal{C}_A = \{y_i(t),\, t \in [0, A] \,|\, i \in \mathcal{I}_A\}, \quad A = A_1, \ldots, A_k. \quad (1)$$

The particular values of the age intervals considered for the analysis are specified in Section 3. Now the idea is to analyse separately each group of curves. In the following we describe the functional data analysis techniques that we will use, and in Section 3 we present the results of the analysis performed on the different groups and the comparisons between them.

2.1 Estimating the central trend

Providing a measure of centrality when dealing with functional data is not an straightforward task. Indeed, not only the levels of the curves matter, but also their shapes, whose information is more difficult to incorporate to any numerical summary. The problem aggravates if we consider curves for which the main features are not aligned. It is well known that in this context, the sample point-wise or cross-sectional mean is a poor estimator of the mean behaviour (Gasser *et al.*, 1984; Kneip and Gasser, 1992; Gasser and Kneip, 1995). A very simple example of that is to consider two bell-shaped curves, $y_1(t)$ and $y_2(t)$, with different and distant modes. The point-wise or cross-sectional mean of these two curves, that is, $\bar{y}(t) = 0.5(y_1(t) + y_2(t))$, will probably present two modes, and then will not look alike, in terms of shape, any of the two curves.

In this context, it is extremely important to use measures of centrality that can take into account the misalignment between the curves of the sample. Indeed, in the particular case of the dependency evolution curves that we study in this work, it is very natural to consider that the evolution of dependency may present a common pattern which is accelerated or retarded in some individuals with respect to others. Then, it is useful to consider the following *time warping* model for the generation of the observed curves:

$$y_i(t) = x_i \circ h_i^{-1}(t) \quad t \in [0, A], \quad i = 1, \dots, n, \tag{2}$$

where x_i are i.i.d. realizations of the process of interest and h_i^{-1} are the so-called *warping* functions that represent individual time distortion. In the *time-warping* model, two approaches to estimate the central trend or mean behaviour of the data are possible: 1) to align or register the curves, that is, to estimate x_i, and to compute any desired sample statistic on the registered sample, $\hat{x}_1, \dots, \hat{x}_n$; and 2) to define appropriate estimators directly on the observed sample, taking into account the nature of the data. For the analysis of the dependency data set we will consider one estimator of each kind that we now describe.

2.1.1 Cross-sectional mean after registration

Aligning or registering the trajectories consists in estimating the warping functions to get $\hat{x}_i(t) = y_i(\hat{h}_i(t))$, $i = 1, \dots, n,$. There exist many different curve registration methods adapted for different scenarios, most of them requiring densely observed data and smoothness (Kneip and Gasser (1992); Silverman (1995); Ramsay and Li (1998); Kneip and Ramsay (2008); see Ramsay and Silverman (2005), Chapter 7, for an overview). For instance, if one can clearly identify the same common features in all the curves, landmark registration, which consists on estimating the warping functions such that those features are brought together, is the benchmark. However, in our case we deal with sparsely and irregularly observed functional data for which landmarks are not clearly identified. In this framework, the method presented in Arribas-Gil and Müller (2012) is specially designed to align this kind of curves. It consists on three steps:

1. For every pair of curves, y_i and y_j, find the correspondence between sequences $y_{i1}, \dots, y_{in_i}$ and $y_{j1}, \dots, y_{jn_j}$ that minimizes a dissimilarity criterion. At this step, for each two individuals we only look for similarities at their sequences of scale values, regardless of the time vectors $t_{i1}, \dots, t_{in_i}$ and $t_{j1}, \dots, t_{jn_j}$ at which these have been recorded. This "similarity matching" is performed through a discrete dynamic time-warping algorithm.

2. Once we have the correspondence between the values of curves y_i and y_j we define functions $\hat{g}_{ji}(t_{ih}) = t_{jM(N^{-1}(h))}$, $h = 1 \dots, n_i$, and $\hat{g}_{ij}(t_{jl}) = t_{iN(M^{-1}(l))}$, $l = 1 \dots, n_j$, which are a transformation of the time scale of curve y_i towards that of curve y_j, and vice versa. That is, $(\hat{g}_{ji}(t_{ih}), y_{ih})_h$ is aligned to $(t_{jl}, y_{jl})_l$ and $(\hat{g}_{ij}(t_{jl}), y_{jl})_l$ is aligned to $(t_{ih}, y_{ih})_h$.

3. After repeating steps 1 and 2 for every possible pair of curves, following Rong and Müller (2008) we estimate the warping functions as follows:

   $$\hat{h}_i^{-1}(t_{ih}) = \frac{1}{n-1} \sum_{j \neq i} \hat{g}_{ji}(t_{ih}), \quad h = 1, \dots, n_i, \quad i = 1, \dots, n.$$

   The registered or aligned curves are then:

   $$\hat{x}_i(t_{ih}) = y_i \circ \hat{h}_i(t_{ih}), \quad h = 1, \dots, n_i, \quad i = 1, \dots, n.$$

The whole algorithm has a computational complexity of $O(\binom{n}{2}L^2) \approx O((n \cdot L)^2)$, ($L$ standing for some average number of observed points per curve). For more details on the method see Arribas-Gil and Müller (2012).

Once we have aligned the sample of curves we can compute any sample statistics such as the cross-sectional mean of the registered sample.

2.1.2 Deepest curve

The literature on estimators of the second kind, namely, those directly defined on the unregistered sample, is relatively small. We can cite Dupuy, Loubes, and Maza (2011), Liu and Müller (2004) or Arribas-Gil and Romo (2012) as works particularly concerned by the definition of suitable population centrality measures, and their corresponding sample statistics, in the *time-warping* model.
For the analysis of the dependency data set we will consider the approach of Arribas-Gil and Romo (2012) since it provides a robust estimator of the central trend for a set of curves. Indeed, the registration procedure described in Section 2.1.1 neutralises the effect of those curves with an atypical shape (due to the fact that they may be retarded or accelerated with respect to the rest). However, there might be curves with a typical shape but taking atypical values (abnormally high or low at some locations). A way to provide a centrality measure that is robust against the two types of atypical curves is to use functional depth. Indeed the deepest curve of a sample, in terms of band depth (López-Pintado and Romo, 2009), has been proved to be an accurate and robust estimator of the central pattern of a sample of curves in the time warping model (Arribas-Gil and Romo, 2012). It can be understood as a generalization of the median to functional data because, intuitively, it is the curve most surrounded by other curves. Therefore, it provides an accurate measure of centrality since: (i) it is a curve geometrically located in the center of the sample and (ii) it presents a typical shape because it is one of the observed curves. These properties make it a robust estimator, against the two types of functional atypical observations above described, even when computed on an un-registered sample.

In the analysis of Section 3 we compare, for each group of curves, the sample mean (computed after registration) and the deepest curve (computed directly on the original sample before registration). Let us finally point out that all the procedures above described (registration, determination of the deepest curve and sample mean calculation) have been adapted in the straightforward way in order to take into account the weighted sampling, that is, the fact that each individual in the sample represents a different number of individuals in the population.

2.2 Curve clustering

In the time warping model (2) warping function estimates are useful for individuals classification. Indeed, they contain information on how different a curve is with respect to the rest in terms of how accelerated or retarded has the process been registered in that particular individual. Then, following Arribas-Gil and Müller (2012) we will perform distance-based clustering of individual curves using the warping functions to define a distance among individuals. Indeed, we define

$$d(i,j) = \int_0^A \left(\hat{h}_i^{-1}(t) - \hat{h}_j^{-1}(t)\right)^2 dt, \quad i,j = 1\ldots,n. \tag{3}$$

Since warping function estimates are discrete-valued functions, the integral needs to be computed numerically. Instead of using classical Multidimensional Scaling for dimension reduction we propose to work directly with this distance matrix to obtain groups of individuals with similar profiles. For this, we use a k-means algorithm in which the centroids of the clusters are defined as those individuals that minimise the total sum of square distances to rest of individuals in the same cluster.

2.3 Forecasting of dependency scores

Once we have a common evolution pattern for each group of age, these will be the base to estimate future scores. Due to the division of the sample into different age groups, the resulting average or deepest curves obtained as explained in Section 2.1 exhibit a special structure. Indeed we have, for age intervals $[A, A+5]$ a representative curve f_A defined in $[0, A]$, $A = A_1, \ldots, A_k$. Taking into account that in practice each curve is a series of discretised values, we could summarise all the information in a $k \times k$ table where each row represents an age group or cohort, and each column stands for a time point. That is, row j will contain j values, $f_{A_j}(A_1), \ldots, f_{A_j}(A_j)$, leaving the last $k-j$ columns empty. The resulting table has an structure similar to that of a run-off triangle. This tool is quite usual in the actuarial practice to estimate the level of reserves necessaries to face potential claims in the future. So, the projected scores can be obtained using techniques that can be appropriate in this context, such as the *Chain Ladder* technique (see for instance Taylor (1986)). However, the application of this method could lead to non desirable results in our case, that is, it would be possible to get scores greater than 100 points which will be inconsistent with the definition of dependency that we are considering. For this reason, and following the Brass logit model (Brass (1971)), chain ladder will be used on the logits of the scores. After finding the scores from the logits, the output of the method is just the expected scores for the cohorts at certain future ages. Confidence intervals will be estimated for every forecast using bootstrap. To this end, we will follow the approach proposed by England and Verrall (1999).

3 Analysis of dependency evolution data

As explained in Section 2, the first step of the analysis is to divide the individuals of the sample into groups of people in terms of their age. As we are interested in the older population, we consider the age intervals $[50, 55)$, $[55, 60)$, $[60, 65)$, $[65, 70)$, $[70, 75)$, $[75, 80)$, $[80, 85)$, $[85, 90)$, $[90, 95)$, and $[95, \infty)$. That is, we define a collection of 10 groups of individuals $\{\mathcal{I}_A\}_{A\in\mathcal{A}}$ and their corresponding groups of dependency evolution curves $\{\mathcal{C}_A\}_{A\in\mathcal{A}}$, with $\mathcal{A} = \{50, 55, 60, 65, 70, 75, 80, 85, 90, 95\}$. In Figure 2 we present the curves in the different groups of age, before and after alignment by the technique described in Section 2.1.

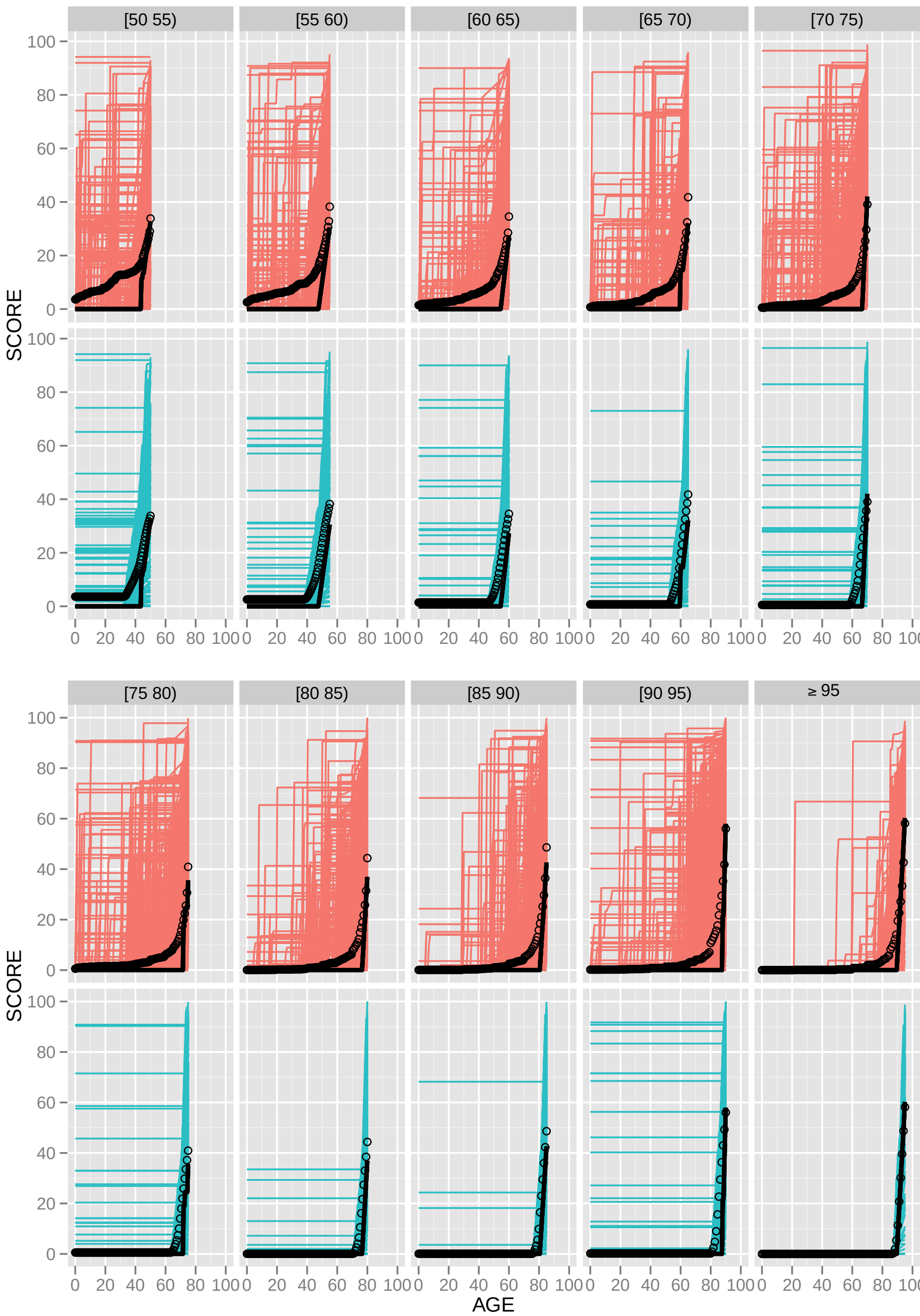

Figure 2: Top: dependency evolution curves by age intervals. Black circles represent the cross-sectional mean of the observed curves and solid black line stands for the deepest curve of the sample. Bottom: Aligned dependency evolution curves by age intervals. Black circles represent the cross-sectional mean of the registered curves and solid black line stands for the deepest curve of the sample.

3.1 Data analysis of the whole data set

For each one of the age intervals previously defined we have computed the cross-sectional mean, the cross-sectional mean of the registered curves and the deepest curve. These are displayed in Figure 2 . It can be seen that in every subsample the cross-sectional mean before registration takes higher scores at younger ages than the cross-sectional mean after registration. This is due to the presence of some atypical individuals for which high scores are reached at early ages. Their influence is reduced by aligning the curves. However, there is another kind of atypical individuals: those who take very high scores at typical ages. Their effect can not be attenuated by the registration process, since their temporal behaviour is standard. This point can be dealt by using a robust measure such as the deepest curve in each subsample. Indeed, we observe that for every age interval the deepest curve is systematically lower (during the whole time interval) than any of the cross-sectional means. This indicates that the distribution of dependency evolution might present a slight positive asymmetry. However, the difference between the deepest curve and the mean of the registered trajectories is small and almost negligeable for many of the age groups. So from now on, and for the sake of interpretability, all our analysis will be based on the mean after registration.

3.2 Differences by gender

The data set is composed by 6226 women and 3266 men, that represent, due to the weighted sampling, 466031 women and 213752 men in the population. We now consider them separately to study the differences in their evolution profiles. We repeat the analysis performed to the whole sample, now applied to the gender groups. After defining, for men and women, the different age groups, we obtain the mean curves shown in Figure 3. Let us look at men mean curves for a moment. We can see that the mean score at 70 for men with ages in $[70, 75)$ is lower than the mean score at 75 for men with ages in $[75, 80)$, and this one lower than the mean score at 80 for men with ages in $[80, 85)$, and so on. That is, in general, the end-point of each mean curve is lower or equal the end-point of the next one. The same holds for the women mean curves. So we could say that the dependency situation of a person gets worse with age, as expected. However, each one of the curves is somehow *retarded* with respect to the previous one. That is, when comparing two curves corresponding to two different age groups, any given score is systematically reached later (at an older age) by the group with older people. For instance, let us compare the score at 70 years old of the group composed by men with ages in $[70, 75)$ and the group of men with ages in $[80, 85)$. The mean score in the group $[80, 85)$ at 70 years old is almost zero, whereas the mean score at 70 in the group $[70, 75)$ is over 40 points. That is, people with ages in $[70, 75)$ present at 70 years old a worse situation than those with ages in $[80, 85)$. This is a consequence of the survey design and reflects that once the dependency appears there is no possibility to reduce its intensity, measured by the score.

As for differences between men and women we can say that in the first groups of age (until 70 years old) men evolve earlier than women in their dependency situation and even have slightly higher final scores, excepting for the group of people aged between 60 and 65 in which

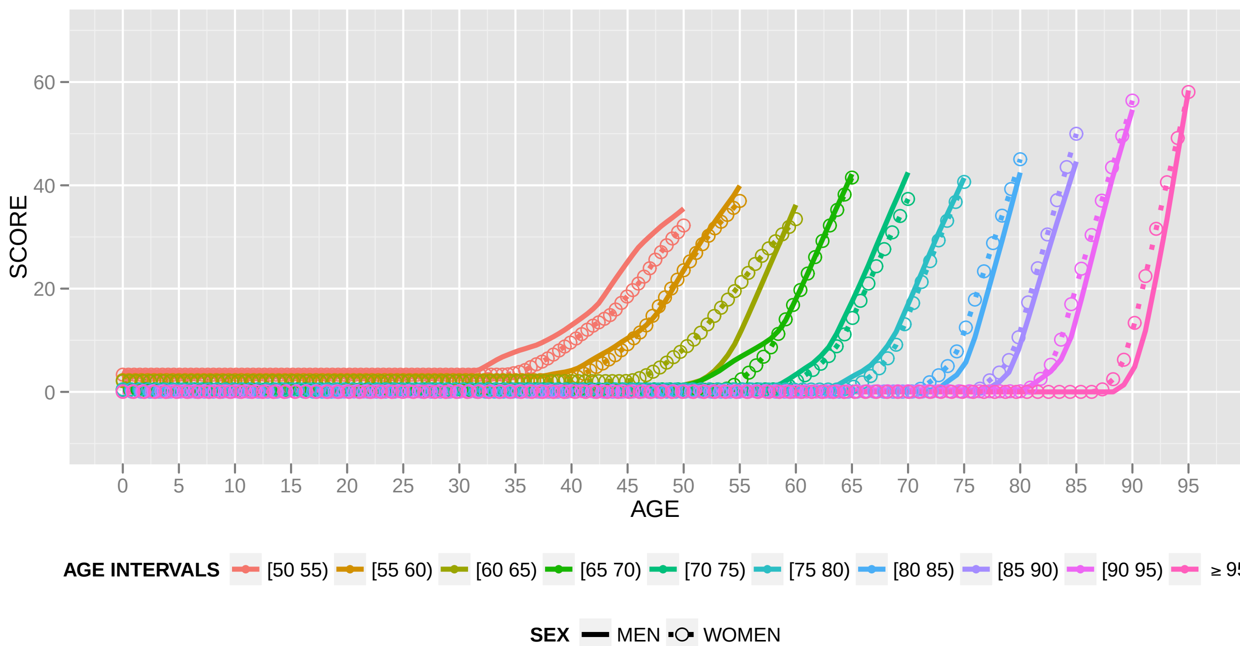

Figure 3: Cross-sectional means after registration for men (solid lines) and women (circles) for the 10 different age groups.

this situation reverses. However, for people older than 75 year old, the situation is quite the opposite: men worsen slower and reach lower final scores than women.

We have to point out that the mean for men and women has been calculated by registering separately the two sets of curves within each age group. That is, we have considered for each age interval the original trajectories observed for men and women, we have then aligned them separately obtaining two sets of registered curves, and we have computed the cross-sectional mean in each of these sets. This is different to jointly align all the curves (as shown in Figure 2) and then averaging separately the registered curves corresponding to men and those corresponding to women. Indeed, the registration process eliminates time distortion among individuals. However, if the distortion is due to the presence of different subpopulations and not only to sample variability, we will be interested in keeping those differences. To that end, we need to register separately the different subpopulations since the global registration procedure will produce an undesirable homogenization effect.

3.3 Identification of profiles

With the aim of identifying different profiles in the dependency evolution of the individuals of the sample, we have performed a warping-based clustering analysis, as explained in Section 2.2. For this we use the warping function estimates obtained for each one of the original age intervals $[50, 55)$, $[55, 60)$, $[60, 65)$, $[65, 70)$, $[70, 75)$, $[75, 80)$, $[80, 85)$, $[85, 90)$, $[90, 95)$, and $[95, \infty)$, that is, without considering any differentiation in terms of gender or age of first occurrence. We then apply a k-means type clustering algorithm to the distance matrix $D = (d(i, j))_{i,j}$. We can clearly identify two clusters of dependency curves for each age interval, which are shown in Figure 4. The conclusions are similar for any of these age groups: the first, and less numerous, cluster corresponds to individuals with *early-onset* dependency and many jumps homogeneously distributed along their lives. The second cluster contains the most common profile, which consist of individuals with *regular* dependency or *early-onset* dependency but with very few jumps concentrated at the end of their life. That is, the two clusters do no exactly correspond to *early-onset* and *regular* dependency evolution, but to individuals with a continuous worsening and individuals with a decay mostly concentrated at the end of their lives, which represent the majority of the population. If we now consider, within each group of age, the two clusters, we can analyse the differences between them. The means after registration for the two profiles are presented in Figure 5. As we explained above for the means by gender, these means are obtained by registering separately the trajectories of cluster 1 and cluster 2 within each age group. We can see how mean trajectories for the first cluster exhibit a faster increase reaching higher scores much earlier in time than those for the second cluster. However, for the groups of older individuals (past 80 year old) the mean final scores in both clusters tend to get closer. That is, it seems that the differences between the two profiles reduce as individuals get older. An exception to this appears in the last group of age, namely that with individuals older than 95, in which the difference between the two clusters is very important. However, this fact should be taken with caution since the first cluster in this group contains only 8 individuals.

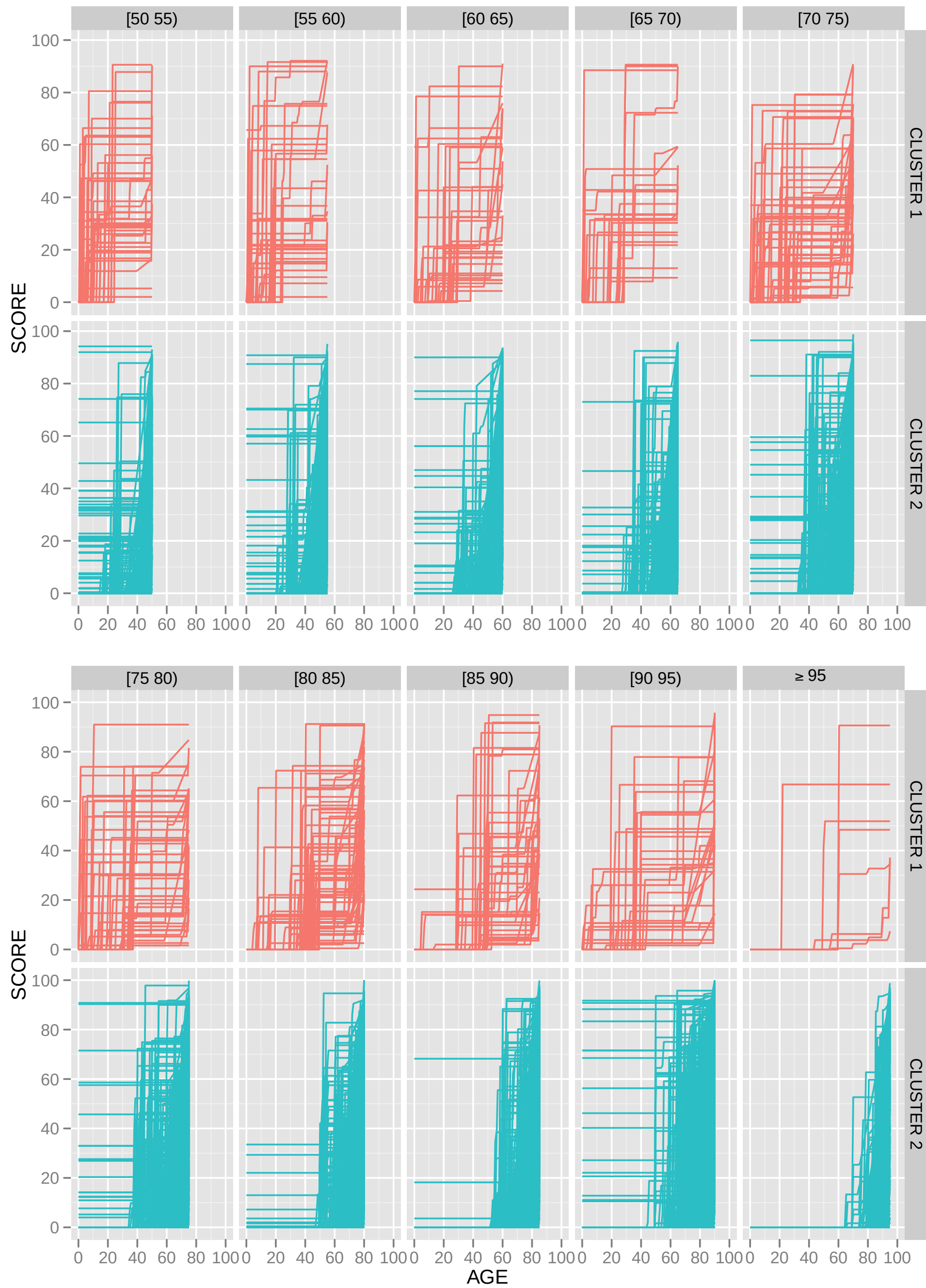

Figure 4: Dependency evolution curves in the two clusters by age intervals.

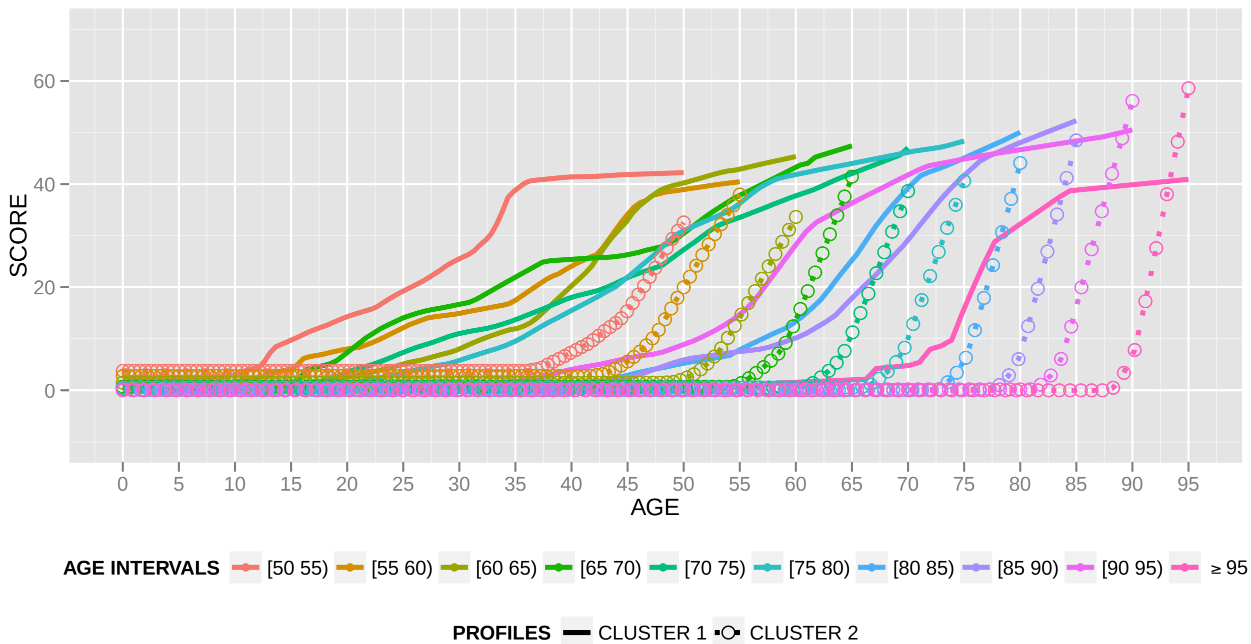

Figure 5: Cross-sectional means after registration for individuals in the first (solid lines) and second cluster (circles) for the different age intervals.

3.4 Forecasting of dependency scores

As it was explained in Section 2.3, forecasting will be achieved by the chain ladder method together with bootstrap to build confidence intervals. The first step is get the logit of each known average score, S_{it}, where i refers to the group of age, and t stands for time. We define $l_{it} = log((S_{max} - S_{it})/(S_{it} - S_{min}))$, where S_{max} is equals 100 and S_{min} is equal to $S_{i,t-1}$, that is, the previous average score in the same group of age, with $i = 50, 55, \ldots, 95$ and $t = i, i{+}5, \ldots, 95$. With this setting we ensure that every future score is at least equal to the previous one.
As the chain ladder will be used on logits, the whole set of required information to compute them will include 65 average score values, and the set of logits on which the technique will be implemented is composed by 55 values.

Once the future logits have been estimated the projected scores are obtained as $\hat{S}_{i,t} = (S_{max} + S_{min}exp(\hat{l_{it}}))/(1 + exp(\hat{l_{it}}))$. The confidence interval for each prediction has been built using bootstrap with a number of bootstrapped samples equal to 10,000 times. In Tables 2, 3 and 4 we present the results by cluster and by gender and cluster.

Looking at the different rows of the tables, for any given cohort forecasted scores grow with age as expected. If we now focus on columns, for any given future age, scores get smaller as the cohorts ages get closer to that age. That is, the younger a person becomes a dependent, the higher the scores they will reach in the future. By profiles, individuals in the first cluster will reach higher scores than those in the second one, except for the oldest cohorts and very advanced future ages.
Combining sex and profiles, women behave similarly to the the global population, that is, higher scores are expected in the first cluster except for forecasts for 95 year old when individuals are over 65. However for men the results are quite the opposite since the highest scores are expected in the second cluster.

4 Discussion

Interest related to disability and dependency issues has increased during the last years, not only in its medical aspects but also, and specifically, in those referring to social and economic matters. Deteriorating physical conditions due to ageing, made worse in some cases by physical and/or mental limitations, represents a huge problem for a continually ageing society as a whole. This needs to be considered if we wish to find a set of possible solutions to these issues. The time to address this problem is already at hand, although the projected age structure for population suggests that it will become an even more serious issue in the next decades.

Therefore, it would seem quite appropriate to address the future situation of those affected by the contingency of dependency. The first step to achieve this is to have good statistical support that helps us describe the present situation of those in both situations: disability and/or dependency. It is necessary to remind the reader that the definitions of these two concepts used in this paper are those reflected in the Spanish regulations. By those definitions every depen-

Table 2: Forecasted scores by cluster. All the ages in the table reflect the beginning of each interval. For each age, the upper, central and lower lines show the lower limit, average forecasted score and the upper limit, respectively. All the intervals has been estimated at a 95% confidence level.

	Cluster 1									Cluster 2								
Age	55	60	65	70	75	80	85	90	95	55	60	65	70	75	80	85	90	95
	42.75	47.46	53.28	60.46	68.26	75.61	82.22	87.71	91.90	30.11	34.26	39.51	46.13	54.71	64.53	74.33	83.02	90.40
50	48.68	57.83	66.37	74.21	81.16	86.95	91.37	94.61	96.86	36.52	45.51	54.60	63.79	72.75	80.83	87.48	92.49	96.05
	54.77	67.55	77.59	85.17	90.59	94.49	97.02	98.61	99.85	72.73	89.41	95.74	98.23	99.23	99.65	99.84	99.92	99.96
	-	41.06	45.31	50.69	57.39	65.39	73.44	80.80	87.41	-	30.84	34.23	39.02	46.22	55.21	65.79	76.29	86.60
55	-	49.06	58.96	68.00	76.15	83.12	88.59	92.74	95.71	-	40.23	49.86	59.21	68.49	77.19	84.68	90.60	95.03
	-	75.51	89.95	95.82	98.20	99.20	99.64	99.84	99.94	-	80.98	94.38	98.17	99.33	99.73	99.88	99.94	99.97
	-	-	40.33	44.50	50.02	57.06	65.02	73.21	81.73	-	-	31.41	34.58	39.97	48.10	58.34	70.33	82.73
60	-	-	49.46	59.83	69.26	77.62	84.44	89.84	93.87	-	-	42.92	53.46	63.47	72.96	81.41	88.36	93.78
	-	-	78.87	92.31	97.06	98.81	99.50	99.78	99.91	-	-	83.31	95.53	98.60	99.51	99.81	99.91	99.96
	-	-	-	42.79	46.41	51.96	58.71	66.73	75.75	-	-	-	33.89	37.64	43.83	53.24	65.24	79.53
65	-	-	-	52.63	62.84	72.07	79.94	86.47	91.62	-	-	-	48.05	59.40	69.56	78.67	86.39	92.70
	-	-	-	81.13	93.35	97.49	99.04	99.61	99.87	-	-	-	88.29	97.36	99.25	99.75	99.90	99.95
	-	-	-	-	42.90	46.80	52.05	59.10	68.30	-	-	-	-	35.46	39.52	46.86	58.05	74.07
70	-	-	-	-	53.46	64.21	73.52	81.64	88.32	-	-	-	-	51.65	63.61	73.94	82.98	90.78
	-	-	-	-	81.92	93.77	97.69	99.13	99.77	-	-	-	-	91.00	98.26	99.53	99.85	99.93
	-	-	-	-	-	41.87	46.34	53.36	62.30	-	-	-	-	-	38.81	43.30	52.21	69.63
75	-	-	-	-	-	55.65	67.71	77.70	85.78	-	-	-	-	-	55.20	67.20	77.85	87.86
	-	-	-	-	-	85.75	96.12	98.82	99.70	-	-	-	-	-	92.86	98.61	99.58	99.86
	-	-	-	-	-	-	40.11	44.62	52.37	-	-	-	-	-	-	37.46	43.89	60.93
80	-	-	-	-	-	-	55.43	68.70	79.68	-	-	-	-	-	-	56.05	69.87	83.27
	-	-	-	-	-	-	87.44	97.15	99.60	-	-	-	-	-	-	93.75	98.74	99.56
	-	-	-	-	-	-	-	43.83	48.16	-	-	-	-	-	-	-	41.82	55.76
85	-	-	-	-	-	-	-	58.73	72.00	-	-	-	-	-	-	-	61.30	78.38
	-	-	-	-	-	-	-	89.96	99.48	-	-	-	-	-	-	-	94.60	98.61
	-	-	-	-	-	-	-	-	40.71	-	-	-	-	-	-	-	-	48.69
90	-	-	-	-	-	-	-	-	60.76	-	-	-	-	-	-	-	-	68.67
	-	-	-	-	-	-	-	-	97.58	-	-	-	-	-	-	-	-	97.92

Table 3: Forecasted scores for men by cluster. All the ages in the table reflect the beginning of each interval. For each age, the upper, central and lower lines show the lower limit, average forecasted score and the upper limit, respectively. All the intervals has been estimated at a 95% confidence level.

	Cluster 1: men									Cluster 2: men								
Age	55	60	65	70	75	80	85	90	95	55	60	65	70	75	80	85	90	95
	37.80	44.69	52.08	59.57	67.26	74.27	80.32	85.54	89.80	30.23	30.87	31.81	33.17	35.92	40.32	47.63	55.17	67.93
50	42.34	52.47	61.71	70.09	77.44	83.63	88.47	92.21	95.02	45.28	53.83	61.36	68.72	75.92	82.51	87.95	91.84	94.89
	51.04	65.88	76.76	84.67	90.11	93.85	96.26	97.84	98.96	98.92	99.97	99.99	99.99	99.99	100.00	100.00	100.00	100.00
	-	36.83	40.83	45.98	52.12	59.10	66.00	72.90	79.39	-	30.83	30.83	30.83	30.93	31.49	33.34	36.51	41.83
55	-	42.03	50.36	58.61	66.61	74.09	80.51	85.99	90.53	-	46.16	53.05	59.74	66.96	74.33	81.27	86.64	91.16
	-	58.49	74.46	84.64	90.94	94.78	97.02	98.34	99.20	-	99.99	100.00	100.00	100.00	100.00	100.00	100.00	100.00
	-	-	36.26	40.56	45.85	52.54	59.41	66.12	73.44	-	-	28.85	28.85	28.85	28.86	29.30	30.70	35.05
60	-	-	42.17	51.16	59.95	68.32	75.69	82.18	87.73	-	-	50.46	58.21	65.41	72.77	79.65	85.12	89.98
	-	-	60.24	76.83	86.68	92.54	95.91	97.82	98.94	-	-	99.99	100.00	100.00	100.00	100.00	100.00	100.00
	-	-	-	37.96	41.40	46.14	51.51	57.78	64.82	-	-	-	33.87	33.87	33.87	33.88	34.05	35.92
65	-	-	-	43.74	52.09	60.51	68.36	75.81	82.67	-	-	-	56.48	64.41	71.84	78.82	84.36	89.51
	-	-	-	60.36	76.26	86.07	92.04	95.69	97.99	-	-	-	99.99	100.00	100.00	100.00	100.00	100.00
	-	-	-	-	36.94	41.36	46.63	53.08	60.37	-	-	-	-	34.60	34.60	34.60	34.60	34.98
70	-	-	-	-	45.19	55.58	64.77	73.22	80.86	-	-	-	-	62.69	71.31	78.65	84.14	88.93
	-	-	-	-	66.58	83.16	91.51	95.77	98.15	-	-	-	-	99.99	100.00	100.00	100.00	100.00
	-	-	-	-	-	37.59	41.41	46.60	53.48	-	-	-	-	-	37.69	37.69	37.69	37.70
75	-	-	-	-	-	46.36	56.41	65.92	74.99	-	-	-	-	-	65.52	74.45	80.65	86.28
	-	-	-	-	-	67.51	83.80	92.11	96.89	-	-	-	-	-	100.00	100.00	100.00	100.00
	-	-	-	-	-	-	35.86	40.17	46.14	-	-	-	-	-	-	34.75	34.75	34.75
80	-	-	-	-	-	-	46.31	57.99	68.95	-	-	-	-	-	-	65.25	73.98	81.68
	-	-	-	-	-	-	71.48	87.62	95.17	-	-	-	-	-	-	100.00	100.00	100.00
	-	-	-	-	-	-	-	38.53	41.86	-	-	-	-	-	-	-	15.16	15.16
85	-	-	-	-	-	-	-	47.70	59.24	-	-	-	-	-	-	-	54.51	68.16
	-	-	-	-	-	-	-	70.52	90.20	-	-	-	-	-	-	-	100.00	100.00
	-	-	-	-	-	-	-	-	36.70	-	-	-	-	-	-	-	-	43.39
90	-	-	-	-	-	-	-	-	49.91	-	-	-	-	-	-	-	-	70.95
	-	-	-	-	-	-	-	-	82.74	-	-	-	-	-	-	-	-	100.00

Table 4: Forecasted scores for women by cluster. All the ages in the table reflect the beginning of each interval. For each age, the upper, central and lower lines show the lower limit, average forecasted score and the upper limit, respectively. All the intervals has been estimated at a 95% confidence level.

	Cluster 1: women									Cluster 2: women								
Age	55	60	65	70	75	80	85	90	95	55	60	65	70	75	80	85	90	95
	47.40	51.82	56.68	62.33	69.38	76.21	82.41	87.54	91.72	28.31	32.56	38.08	45.00	53.80	63.65	73.78	82.66	90.41
50	52.81	61.20	69.02	76.23	82.66	88.05	92.15	95.10	97.15	34.64	43.75	53.13	62.58	71.80	80.13	87.02	92.21	95.90
	75.98	89.55	95.35	97.89	99.02	99.54	99.78	99.89	99.95	63.16	81.84	91.03	95.56	97.79	98.90	99.45	99.72	99.86
	-	43.05	47.69	53.66	61.22	70.02	77.90	84.27	89.65	-	29.47	33.06	38.17	45.52	55.01	65.92	76.53	86.77
55	-	53.07	63.88	72.99	80.66	86.86	91.47	94.70	96.93	-	38.60	48.39	57.94	67.47	76.44	84.19	90.32	94.87
	-	82.29	94.38	98.05	99.27	99.70	99.87	99.94	99.98	-	80.80	94.39	98.19	99.35	99.74	99.89	99.95	99.97
	-	-	43.06	46.59	51.92	58.73	66.68	74.87	82.28	-	-	31.04	34.10	39.08	46.90	57.09	69.17	82.07
60	-	-	53.66	63.82	72.71	80.45	86.67	91.37	94.85	-	-	41.70	51.68	61.49	71.12	79.93	87.36	93.23
	-	-	81.94	94.03	97.86	99.15	99.65	99.86	99.95	-	-	84.85	96.21	98.91	99.63	99.85	99.94	99.97
	-	-	-	45.61	49.19	54.81	61.45	69.07	77.81	-	-	-	32.70	36.92	43.70	53.35	65.73	80.14
65	-	-	-	56.49	66.54	75.35	82.68	88.48	92.99	-	-	-	47.43	59.24	69.68	78.91	86.64	92.84
	-	-	-	85.02	95.26	98.29	99.36	99.76	99.94	-	-	-	90.32	98.12	99.54	99.85	99.94	99.97
	-	-	-	-	45.97	49.42	54.56	60.99	69.80	-	-	-	-	34.91	39.37	46.80	58.16	74.48
70	-	-	-	-	57.44	67.86	76.68	83.97	89.97	-	-	-	-	50.10	62.17	72.87	82.32	90.41
	-	-	-	-	84.87	95.43	98.44	99.48	99.93	-	-	-	-	91.68	98.50	99.61	99.86	99.94
	-	-	-	-	-	44.08	47.91	53.83	62.91	-	-	-	-	-	38.39	43.31	52.47	69.43
75	-	-	-	-	-	58.99	70.59	79.68	87.27	-	-	-	-	-	54.46	66.62	77.50	87.62
	-	-	-	-	-	89.86	97.78	99.50	99.95	-	-	-	-	-	93.04	98.74	99.64	99.85
	-	-	-	-	-	-	41.32	45.37	52.96	-	-	-	-	-	-	37.54	43.84	60.57
80	-	-	-	-	-	-	58.77	71.45	81.87	-	-	-	-	-	-	56.11	70.01	83.34
	-	-	-	-	-	-	91.49	98.85	99.95	-	-	-	-	-	-	93.70	98.77	99.56
	-	-	-	-	-	-	-	43.58	47.27	-	-	-	-	-	-	-	42.35	56.27
85	-	-	-	-	-	-	-	61.83	75.32	-	-	-	-	-	-	-	61.18	78.23
	-	-	-	-	-	-	-	96.32	99.98	-	-	-	-	-	-	-	94.86	98.93
	-	-	-	-	-	-	-	-	44.32	-	-	-	-	-	-	-	-	48.12
90	-	-	-	-	-	-	-	-	64.36	-	-	-	-	-	-	-	-	68.54
	-	-	-	-	-	-	-	-	99.87	-	-	-	-	-	-	-	-	96.73

dent person suffers several kinds of disability (which may be specifically age-related), whereas the opposite is not always true; That is, not all disabled individuals are dependent. Since 1986, the study of disability in Spain has been mainly addressed by the National Disability Surveys undertaken by INE. Before that, the Spanish population censuses had included some questions about the incidence of disability among the population, but with no sufficient consistency. This was the basic reason that motivated INE to prepare a survey about this matter. Until now, three surveys have been undertaken. The first one was carried out in 1986 in conjunction with the Elder Institute and Social Services (IMSERSO), following the WHO International Classification of Impairments, Disabilities and Handicaps. This classification was the first to establish an official conceptual framework for disability with a common and universal language. Thirteen years later, INE, IMSERSO and ONCE Foundation (Spanish Blind National Organization), all together, prepared the second survey about disabilities, called EDDES-99. Although this new survey can be considered more complete than that of 1986, its different methodology made it impossible to do some comparison between them (INE, 2010). Finally, the last survey was launched in 2008. The EDAD 2008 is not only the most important database on disability among the Spanish population, but is arguably one of the most complete, periodic, national population approaches to studying disability worldwide. Major differences between the EDAD 2008 and previous disability surveys in Spain pertain to the former's target of providing additional information on functional dependency in order to support planning and funding of the Spanish dependency system (Maierhofer *et al.* (2011)). As demonstrated in the 1999 survey, the differences in methodology between it and the former studies make it impossible to achieve time continuity of the analysed matter (Meseguer, Vargas, and Mondéjar, 2010). As an example of the differences among them, it can be said that the number of disabilities included in EDDES 1999 was 36, whereas that number increased to 44 in EDAD 2008. In addition, there is not a direct correspondence amongst all of them. As a final conclusion, it must be said that if the aim is to study dependent population over time, a problem exists where longitudinal information is not available. Therefore, the only thing that can be done is to prepare a pseudo panel using the data included in EDAD 2008 (INE (2010)).

To our knowledge, this is the first study in a nationwide scale that makes projections of the individual intensity of this contingency using the definition included in the Spanish Dependency Act of 2006. The results of the forecasts are the expected scores in five year intervals from the present age until a maximum age of 95. There are some previous works on this matter, but they deal with the problem in a more reduced scope. They use small samples focused in just one town, such as Béland and Zunzunegui (1995), Eiroa, Vázquez-Vizoso, and Veras Castro (1996), Graciani *et al.* (2004) and Otero *et al.* (2004). In all these cases, the studies do not try to estimate the future evolution of dependency. They only describe a situation and, because the time at which they were written, do not use the legal definition of dependency. Even the White Book (IMSERSO (2005)), based on the statistical information included in EDDES-99 and prepared by a technical committee to support the Spanish Act, uses a definition of dependency based on the global intensity of disabilities, no matter which these disabilities are. This is quite general and far from the requirements imposed by the subsequent regulations.

The data contained in EDAD 2008 and quantified as explained in Albarrán and Alonso

(2009) provides a dependency evolution trajectory for each individual in the sample, from birth until 2008. However, individuals included in the sample are only those who were dependent at the moment the survey was conducted, so we can not consider their dependency evolution curves as a representation of the general population. For instance, many people in Spain will not be dependent at the age of 60, so the dependency profiles of those 60 year-olds surveyed will not be able to explain their present dependency situation nor to predict their future evolution. To tackle this problem, we have considered evolution dependency profiles in age-homogeneous groups of individuals. Within each group we have applied functional data analysis techniques to summarise the information, since now we have sets of curves defined over the same time intervals. The structure of the resulting data, in the form of run-off triangles, makes it desirable to use actuarial forecasting techniques such as the chain-ladder method.
Our study suggests that, at least for EDAD 2008, two main groups of people can be identified. One group is related to individuals with early-onset dependency. These subjects show many jumps in their scores that are homogeneously distributed throughout their lives. The second group shows the most common profile, which consists of individuals with regular dependency or early-onset dependency but with very few jumps in their scores concentrated toward the end of their lives. This second group contains more subjects than the first. The main difference between them is the rhythm at which the dependency is increasing throughout the lifetime: continuous worsening vs. a rapid decline at the end of the life. This classification in two main groups may be extended to four if gender is considered for each. The differences among dependent people affect their future evolution. Therefore, according to our projections the scores are expected to increase with age. However, for a certain age in the future, the scores are expected to be lower for those cohorts that are near that age at present. That is, the younger a person becomes dependent, the greater the decline seen in the future. Differences are not only present within groups. The gender is the second cause of disparities. Our projections suggest that women will reach higher scores in the future in almost all cases, that is, they will present further dependency.

Disability affects health status and quality of life. It is a significant public health issue all over the world (Lin and Lave (2000)). Due to the clear impact that disability and dependency have on the socio-sanitary system, it is essential to study their prevalence, causes, and effects, in order to formulate a plan for a suitable public health policy (Chalise, Saito, and Kai (2008)). According to the statistical results of this paper, the design of social policies for taking care of these individuals should consider the differences amongst all of them. That is, the amount of resources allocated to dependents will depend on the age at which this contingency appeared, the speed of progression and the gender. In this last matter, it is interesting to note that a higher life expectancy in women is generally accepted, so their necessities of specialized and usually expensive care will be longer in duration. All of these factors should be taken into consideration when planning the financial resource allotment that a society might reserve for adequate attention to these issues, not only now but also in a future characterized by an ageing population in the Western countries.

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