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Household forecasting: Preservation of age patterns

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ABSTRACT

We formulate a time series model of household dynamics for different age groups. We model the shares of the population who are in certain household positions (living alone, living with a partner, etc.). These household positions have very pronounced age patterns. The age profiles change slowly over time, due to changes in the home leaving behaviour of young adults, differences in survival rates of men and women, etc. When forecasting household positions to 2040, we want to preserve the characteristics of the age profiles. We test the Lee–Carter model and the Brass relational method using household data for the Netherlands for the period 1996–2010. Annual shares of the population by household position, age, and sex are modeled as random walks with adrift (RWD). While the Brass model has its limitations, it performs better than the Lee–Carter model in our application. The predicted age patterns based on the Brass model look more reasonable, because the Brass model is a two-parameter model, while the Lee–Carter model contains only one parameter. Also, the model parameters and standard errors of the Brass model are easier to estimate than those of the Lee–Carter model.

1. Motivation

Fig. 1 shows, for the case of The Netherlands in 2011, the proportions of women who live with parents, alone, in a consensual union, or with a marital spouse, broken down by five-year age groups. Most adolescents live with their parents. Those who have left home most often live alone or in a consensual union, up to ages around 30. After that, living with a spouse becomes the dominant position, until ages around 70. Some women become lone mothers, due to separation or divorce. Next, increasing numbers lose their husbands because the husband is a few years older (aggravated by the higher mortality of men), and many elderly women live alone, or together with one or more children. Of women over 95, more than half live in an institution (not shown in the graph).

Age profiles of the type shown in Fig. 1, and their development over time, help us to understand household dynamics. This in turn, when combined with forecasts of future age structures, facilitates demographers in projecting the number of households of various types into the future. Combining population forecasts with future values of carefully selected sets of household parameters is a well-

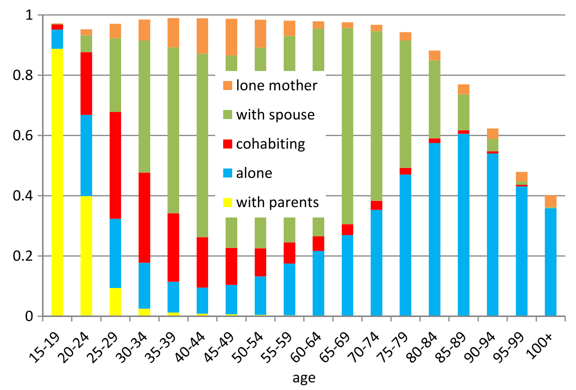

Fig. 1. Proportions of women living in various private household positions, by age; The Netherlands, 2011.
Source: Census data from Eurostat.

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established method of computing household forecasts; see the extensive review by Holmans (2012). In many countries, the life expectancy of men is increasing faster than that of women. What does that imply for the numbers of elderly men and women who live alone? Business cycles and youth unemployment have effects on the home-leaving behaviour of young adults. Formal marriages have become less important in many Western countries since the 1970s, but did consensual unions fill the gap fully or only partially? These and related issues show that it is important to describe and understand the age profiles of various household parameters, when computing household forecasts to be used by policy makers in such diverse fields as housing, social security, consumption, and energy consumption, to name only a few.

Ideally, household forecasts should be based on well-established theories of the household behaviours of individuals. Many scholars have tried to develop social, economic and cultural theories to explain why households change over time. The reasons for such changes include a reduced adherence to strict norms; less religiosity and an increase in individual freedom on ethical issues; female education, which has led to women having greater economic independence, and also facilitates divorce; more assertiveness in favour of symmetrical gender roles; the contribution of women to the labour market; increased economic aspirations; and residential autonomy (Lesthaeghe, 1995; Van de Kaa, 1987; Verdon, 1998). In addition, there are also demographic factors, such as falling levels of fertility, and differences in longevity between men and women. However, none of these theories have resulted in formalized models of household behaviour that are general enough and have sufficient explanatory power to be used for forecasting. Two decades ago, Burch (1995) noted that methods for modelling family and household dynamics had made considerable progress, but that theory had lagged behind considerably. The situation is not much better today, which may reflect the complexity of the subject matter. Thus, as a second best to predicting households based on general behavioural theories, we look for regularities in the observed data, try to understand the trends, and extrapolate them into the future by means of formal time series models. Sometimes the forecaster has very little data, perhaps only one year's worth, upon which the forecast can be based. In that case, a commonly-used approach is simply to keep the parameters of interest constant over the forecast period. One example is the multi-state approach to modelling household dynamics (Van Imhoff & Keilman, 1991), in which the transition probabilities that describe changes among household positions for individuals are kept constant. In the current paper, however, we are able to use time series data over a longer period. This allows us to take possible time trends in the parameters into account explicitly. In addition (though we do not use this here), a time series approach also allows one to make stochastic predictions, and hence to take the prediction uncertainty into account.

The aim of this paper is to show how time series data for the age profiles of men and women in various household positions can be modelled. Using data from The Netherlands for the period 1996–2010, we model the vector of age-specific shares for a certain household position as a random walk with drift (RWD). In other words, we assume that the year-on-year step for the shares consists of a certain fixed term (the drift) plus a normally distributed error term which has a zero expectation. The result is a share with an increasing variance around a linear trend. A random walk with drift model is one type of time series model that has been applied to demography (e.g., Alho & Spencer, 2005). The book by Box and Jenkins (1976) is a standard reference for this and other types of time series models. If one were to model the share of, say, women who live alone as a RWD for each age separately, one would run the risk that the drift terms may be very different for different ages; see Christiansen and Keilman (2013). This would distort the age pattern for these women. In order to retain the age patterns for the household shares, we have selected two methods that were developed originally for mortality analysis, namely the Lee–Carter model (henceforth abbreviated as LC) and the Brass relational method (Brass). We then use the estimated RWD models to extrapolate the shares thirty years ahead.

The contribution this paper makes is to show how data reduction techniques, stemming from mortality analysis, can be used to describe and project household dynamics. More specifically, we show that the Brass method has considerable advantages over LC for this particular data set: the resulting age patterns for men and women in various household positions look more realistic, and the model parameters are easier to estimate.

The remainder of the paper proceeds as follows. In Section 2 we begin by describing the household data, which stem from the population registers of the Netherlands, then outline the LC-model and the Brass approach. Section 3 presents the estimation results, while Section 4 discusses the extrapolated age profiles for future years. We finish the paper in Section 5 with a discussion and conclusions.

2. Data and methods

We are interested in modelling household shares. Write $V(j, x, s, t)$ for the number of people in household position $j = 1, 2, \ldots$ who are of age $x = 0, 1, \ldots$ and sex $s = 1$ or 2, at time $t = 0, 1, 2, \ldots$. Aggregating over position, we obtain the population who are of age x and sex s at time t as $W(x, s, t) = \Sigma_j V(j, x, s, t)$. The share of household position j is $\alpha(j, x, s, t) = V(j, x, s, t)/W(x, s, t) = \alpha_j(x, s, t)$.

2.1. Data

Coen van Duin of Statistics Netherlands kindly supplied us with data from the population registers on the household positions of men ($s = 1$) and women ($s = 2$) in the Netherlands, broken down by age group ($x = 1$ for ages 0–4, $x = 2$ for ages 5–9, …, $x = 20$ for age 95+), as of 1 January of the years 1996 ($t = 1$), 1997 ($t = 2$), …, 2010 ($t = 15$). Following earlier work (Christiansen & Keilman, 2013), we distinguish seven mutually exclusive household positions that an individual can occupy at any given point in time. These household positions are