Studying time use variations using a the life course perspective

Dr. Maroesjka Versantvoort

Leiden University

Faculty of Law

Department of Tax Law and Economics

Steenschuur 25, 2311 ES Leiden

The Netherlands

T +31 71 527 4856

m.c.versantvoort@law.leidenuniv.nl

Summary

Time use variations are analysed by means of Hierarchical Age-Period-Cohort-modelling (HAPC). The authors compare the fixed versus the random-effects model specifications for APC-analysis. The random-effects HAPC-model appears the most appropriate specification. The HAPC analyses find evidence in support of quadratic age effects on time use. Furthermore, the HAPC analyses find significant cohort and period effects. Finally, the period effects as well as the welfare state effects show a non-negligible sensitivity for economic circumstances and welfare policies.

Key-words

Age-Period-Cohort analysis, hierarchical linear modeling, life course, time use, welfare states

1. Introduction

During last years a number of papers appeared that discuss how work and family can be better reconciled by adopting a life-course perspective (for instance Bovenberg, 2005, Naegele et al., 2003, Klammer et al., 2005, Anxo et al., 2006).

The life course perspective, rooted within academic traditions, is an analytical framework that aims to highlight the developmental and dynamic components of human lives, institutions and organisations. One of the main features of the life course approach is to acknowledge the crucial role that time plays in the understanding of individual behaviour and structural changes in society. Another important dimension of the life course approach is its attempt to take a holistic view, so that the analysis no longer views specific events, phases or demographic groups as discrete and fixed but considers the entire life trajectory as the basic framework for analysis (following Anxo et al., 2006, p. 2).

One of the main hypotheses underlying the papers mentioned above is that life courses have changed during last decades (partly) as a result of individualization, industrialization and increased welfare, increased female labour market participation, and ageing of society. Starting from that idea, these papers focus on formulating ideas, concepts, and policies for a new organization of time over (working) life. The (integrated) analysis of variations in life courses during last decades seems to receive far less attention in literature. The work of Liefbroer & Dykstra (2000) for the Netherlands forms an interesting exception however. They describe the life courses of Dutch men and women who grew up in the 20th century, in the light of social events and changes, and emphasize the importance of distinction between period and cohort related changes (following Kronjee, 1990). On this point they go further than Becker (1992, 1997), Easterlin (1980), and Inglehart (1977, 1997) who focus on cohort effects. These scholars argue that the circumstances people experience during their "formative phase" mainly determine their life course. According to Liefbroer and Dykstra period effects are of importance as well; historical changes influence cohorts on various moments in the life course and could be relevant in life phases that have to be passed through in the future.

In this paper we endeavour to throw some more light on the importance of period and cohort effects on variations in life courses by applying a mixed models approach to the age-period-cohort analysis of international time use data, as recently developed by Yang & Land (2006a, 2006b). By means of this approach we are able to separate age, period, and cohort effects, to skirt the "identification problem" characteristic for traditional APC-analyses, and to use the richness of time use micro data available in MTUS[1].

[1] The Multinational Time Use Study (MTUS) was first developed in the early 1980s at the University of Bath, when J. Gershuny observed the potential to harmonise time use datasets collected in the early 1960s through the mid 1980s into a single dataset with common series of background variables and total time spent per day in 41 activities for analysis with the 1965 Szalai Multinational Time Budget Study. The MTUS has grown to encompass over 50 datasets from 19 countries, and is now incorporating recent data from the HETUS, ATUS, and other national level time use projects (http://www.timeuse.org/mtus/).

2. The concepts of age, period, and cohort

For a number of decades, researchers have endeavoured to analyze data using *age* (A) and *time-period* (P) as explanatory variables to study phenomena that are time-specific. An analytic focus in which *cohort* (C) membership, as defined by the period and age at which an individual observation can first enter an age-by-period data array, is also important for substantive understanding (Yang & Land, 2006a, Ryder, 1965). As a result researchers have developed models for situations in which all three age, period, and cohort (APC) are potentially of importance to studying a substantive phenomenon.

Age is synonymous with individual time (following Mulder, 1993). In a strictly operational sense, age is simply the time that has elapsed between the date of birth and the moment of observation. This definition is not of much interest however. As a substitute variable, it can be considered as an indicator of all kind of processes and events associated with growing up and becoming older. In that case it refers to biological phenomena. It can be used as a psychological variable also, as a substitute for increase or decrease of intellectual capacities, development of personality, changing reactions in stress situations, etc. Also it may refer to sociological phenomena: Not until a certain age it is permitted or appropriate to marry and have children; age has to do with the position and the length of participation in social systems (Hagenaars, 1990, Versantvoort, 2000). Thus, *age effects* represent the variation associated with different age groups brought about by physiological changes, accumulation of social experience, and/or role or status changes (Yang & Land, 2006a).

Period is synonymous for historical time. Period, or time, refers to the moments of observation in a purely operational sense. However, also period effects are used as an indicator for the effects of all kinds of discrete events occurring at or between the moments of observation and for the influence of long term processes such as industrialisation, modernization, economic trends, changes in educational standards, etc. So *period effects* represent variation over time periods that affect all age groups simultaneously – often resulting from shifts in social, cultural, economic, or physical environments.

A birth cohort is a group of people born in the same period and experiencing individual time in the same historical time context. There may be compositional differences with regard to background characteristics between cohorts. Cohorts may differ from each other in size also. Some cohorts will differ from each other because they have experienced different events before the first moment of observation. Other cohort differences are caused by the fact that cohorts are affected by the same events and trends but at a different age, and therefore with a different lasting impact (Hagenaars, 1990). In general, *cohort effects* are associated with changes across groups of individuals who experience an initial event such as birth or marriage in the same period; these may reflect the effects of having different formative experiences for successive age groups in successive time periods (Yang & Land, 2006a, based on Robertson et al., 1999, Glenn, 2003).

The age-period-cohort (APC) accounting/ multiple classification model developed by Mason et al. (1973) has served for over three decades as a general methodology for estimating age, period, and cohort effects in demographic and social research. This general methodology focuses on the APC analysis of data in the form of tables of percentages or occurrence/ exposure rates of events. A major methodological "problem" with the APC analysis of tabulated data is that at the operational level there is an exact linear relation among age, period, and cohort: A = P – C. Age is exactly the difference between the moment of observation and data of birth. It is impossible to let one of the factors vary independently of the other two and to have at one particular point in time two persons who have the same age but are "assigned" to different cohorts. Thus, analyses in which all three key variables are included cannot be carried out without further restrictions; the separate effects of age, period, and cohort are not identifiable. This identification problem has drawn great attention in statistical studies of human populations. Various methodological contributions to the specification and estimation of APC models have appeared in recent decades (see for instance, Glenn, 1976, Hobcraft et al., 1982, Fu, 2000, O'Brien, 2000).

In this paper we follow the approach recently proposed by Yang & Land (2006a, 2006b) which offers ample opportunities to both use micro-data (as MTUS data is), to "solve" the identification problem typical for APC-modeling, and to take into account the multi-level structure of the data as well. Micro data in the form of a series of repeated cross-section sample surveys create both new opportunities and challenges to APC analysis. The opportunities lie in the fact that these repeated cross-section survey data not only can be aggregated into population-level contingency tables for conventional multiple classification models but can also provide individual-level data on both the responses and a wide range of covariates, which can be employed for much finer-grained regression analysis. In recognition of the multilevel structure of individual-level responses in repeated cross-section, Yang & Land propose a mixed (fixed and random) effects model approach. In particular, they introduce cross-classified hierarchical linear models (HLM) to represent variations in individual-level responses by periods and cohorts. This leads to the identification and estimation of random effects for period and cohorts that then can become the objects of explanation. This HAPC modeling framework has enhanced the ability to estimate separate age, period, and cohort effects through the estimation of variance components.

3. Time use data

To gain insight in variations in life courses during last decades, and the factors underlying these variations, time use data appear suited. Time use data offer ample possibilities to gain insight in the (relative) importance of various life spheres as paid work, household work, volunteer work/aid, care, and education in and over people's lifes. For policy makers the relevance of an integrated insight in the relation between paid work and these other life spheres seems to have grown with the introduction, acceptation and (policy) application of the idea of transitional labour markets (Schmid, 2000, Schmid and Gazier, 2002)[2].

Data

Time use data are analyzed from several cross-sections of the Multinational Time Use Study (MTUS), 1961-2003, of 18 different countries (see table 1). The data include 275870 respondents who had measures on time use and several covariates across all survey years.

Table 1: Countries and years in MTUS

	Period1 1960-64	Period2 1965-69	Period3 1970-74	Period4 1975-79	Period5 1980-84	Period6 1985-89	Period7 1990-94	Period8 1995-99	Period9 2000-04
Canada			1971		1981	1986	1992	1998	
Denmark	1964					1987			
France			1974					1998	
Netherlands				1975	1980	1985	1990	1995	2000
Norway			1971		1981		1990		2000
UK	1961			1975		1985	1990		2000
USA		1965		1975		1985	1992	1998	2003
Hungary	1965			1977					
Germany	1965						1992		
Poland	1965								

[2] This idea forms one of the pillars underlying life course policies introduced in the Netherlands and Belgium recently.

Belgium	1965								
Czech Rep.	1965								
Yugoslavia	1965								
Italy					1980	1989			
Australia			1974						
Austria							1992		
South Africa									2000
Slovenia									2000

Variables

Besides age, period, and cohort, we distinguish a number of covariates. Time use is assumed to depend on sex, educational level, care for children under age 5, and welfare state. Table 2 presents the covariates and matching descriptive statistics.

Table 2: Descriptive statistics, data 1960-2004, MTUS selection

Variables	Definition	N	Mean	SD	Min	Max
PAID WORK[3]	Time spent on paid work (minutes/ day)	275870	208.89	262.84	0.00	1440.00
EDUCATION[4]	Time spent on education (minutes/day)	275870	23.13	90.14	0.00	1440.00
CHILD CARE[5]	Time spent on child care (minutes/day)	275870	24.37	61.41	0.00	1151.00
HOUSEHOLD[6]	Time spent on household duties (minutes/day)	275870	174.21	157.31	0.00	1343.00
OTHER CARING[7]	Time spent on caring for acquaintances and relatives outside the household (minutes/day)	275870	28.97	68.50	0.00	1085.00
VOLUNTARY[8]	Time spent on voluntary work (minutes/day)	275870	7.03	37.31	0.00	1080.00
LEISURE[9]	Time spent on leisure activities (minutes/day)	275870	290.57	185.42	0.00	1440.00
FEMALE	Sex: 1 = female, 0 = male	275870	0.55	0.49	0.00	1.00
LIBERAL[10]	Liberal welfare state	275870	0.48	0.49	0.00	1.00
CONS[11]	Conservative welfare state	275870	0.28	0.45	0.00	1.00

[3] Consists of the MTUS categories: av1, av2, av3, and av5.
[4] Consists of the MTUS categories: av4 and av33.
[5] Consists of the MTUS category: av11.
[6] Consists of the MTUS categories: av6, av7, av9, av10, and av12.
[7] Consists of the MTUS category: av8.
[8] Consists of the MTUS category: av23.
[9] Consists of the MTUS categories: av17, av18, av19, av20, av21, av24, av25, av26, av27, av28, av29, av30, av31, av32, av34, av35, av36, av38, av39, and av40.
[10] The following countries are assumed liberal welfare states: Canada, United States, United Kingdom, Australia, South Africa.
[11] The following countries are assumed conservative welfare states: France, the Netherlands, Belgium, Germany, West-Germany.

SOCDEM[12]	Socio-democratic welfare state	275870	0.05	0.22	0.00	1.00
SEUR[13]	South European welfare state	275870	0.08	0.27	0.00	1.00
FCOMM[14]	Former communistic welfare state	275870	0.09	0.28	0.00	1.00
EDUC1	No secondary education	275870	0.44	0.49	0.00	1.00
EDUC2	Secondary education completed	275870	0.31	0.46	0.00	1.00
EDUC3	Higher education	275870	0.23	0.42	0.00	1.00
NOCHILD	No children living at home or unknowsn	275870	0.58	0.49	0.00	1.00
CHILD04	Children living at home below age 5	275870	0.15	0.35	0.00	1.00
CHILD5	Children living at home, age 5 or older	275870	0.26	0.44	0.00	1.00
AGE	Age at survey year	275870	40.90	15.22	15.00	74.00
PERIOD	5-year periods	9			1960-1964	2000-2004
COHORT	5-year birth cohorts	19			1895-1899	1985-1989

4. Model and results

4.1 Application of hierarchical APC models to multilevel data

The structure of the age-period-cohort accounting/ multiple classification model / fixed-effects regression model can be written in linear regression form as

$$Y = Xb + \varepsilon, \qquad (1)$$

Where Y is a vector of event/ exposure rates or log-transformed rates from population tabular data, X is the regression design matrix consisting of "dummy variable" column vectors for the vector of model parameters b:

$$B = (\mu,\ \alpha_1,\ \ldots\ \alpha_{\alpha-1}\ ,\beta_1\ ,\ \ldots\ \beta_{\beta-1},\ \gamma_1\ ,\ \ldots,\ \gamma_{\alpha+p-2}\ )^T : \qquad (2)$$

[12] The following countries are assumed socio-democratic welfare states: Denmark, Norway.
[13] The following countries are assumed south-european welfare states: Italy.
[14] The following countries are assumed former communist welfare states: Hungary, Poland, Czech Republic, East Germany, Yugoslavia, Slovenia.

For $i = 1, \ldots, a$ age groups $j = 1, \ldots, p$ periods and μ denotes the intercept or adjusted mean rate; α_i denotes the ith row age effect or the coefficient for the ith age group; β_j denotes the $j$the column period effect or the coefficient for the jth time period; γ_k denotes the kth diagonal cohort effect or the coefficient for the kth cohort for $k = 1, \ldots, (a+p-1)$, with $k = a-i+j$; and ε is a vector of random errors with mean 0 and constant diagonal variance matrix $\sigma^2 I$, where I is and identity matrix. In conventional practice, one of each of the α_i , β_j , and γ_k coefficients is set to zero, thus establishing a "reference" age, period, or cohort category against which the estimated coefficients for the other categories can be compared. As mentioned in the introduction, the key problem in APC analysis using model (1) is the model identification problem. This problem arises in the conventional application of model (1) to tables of percentages or occurrence/exposure rates of events wherein age and period are of equal interval length in the population data and the diagonal cells in the age by period arrays represent the cohorts.

There is an extensive literature on the "solution" of this problem. This literature has identified three conventional strategies for identification and estimation (see for more extensive overview Yang & Land, 2006a):

(1) constraining two or more of the remaining age, period, or cohort coefficients to be equal by placing at least one additional identifying constraint on the parameter vector;

(2) using a "proxy" variable approach that assumes the cohort or period effects are proportional to certain measured variables;

(3) transforming at least one of the age, period, or cohort variables so that its relationship to others is nonlinear.

Considering these strategies, together with the hypothesis that there is a nonlinear age effect on time use, we proceed to specify and test a model of time use as a quadratic function of age.

$$\begin{aligned} PAIDWORK_i = {} & \beta_0 + \beta_1 AGE_i + \beta_2 AGE_i^2 + \beta_3 FEMALE_i + \beta_4 CONS_i + \beta_5 SOCDEM_i + \beta_6 SEUR_i \\ & + \beta_7 FCOMM_i + \beta_8 EDUC2_i + \beta_9 EDUC3_i + \beta_{10} NOCHILD_i + \beta_{11} CHILD5_i + \varepsilon_i \end{aligned} \tag{3a}$$

$$\begin{aligned} EDUCATION_i = {} & \beta_0 + \beta_1 AGE_i + \beta_2 AGE_i^2 + \beta_3 FEMALE_i + \beta_4 CONS_i + \beta_5 SOCDEM_i + \beta_6 SEUR_i \\ & + \beta_7 FCOMM_i + \beta_8 EDUC2_i + \beta_9 EDUC3_i + \beta_{10} NOCHILD_i + \beta_{11} CHILD5_i + \varepsilon_i \end{aligned} \tag{3b}$$

$$\begin{aligned} CHILDCARE_i = {} & \beta_0 + \beta_1 AGE_i + \beta_2 AGE_i^2 + \beta_3 FEMALE_i + \beta_4 CONS_i + \beta_5 SOCDEM_i + \beta_6 SEUR_i \\ & + \beta_7 FCOMM_i + \beta_8 EDUC2_i + \beta_9 EDUC3_i + \beta_{10} NOCHILD_i + \beta_{11} CHILD5_i + \varepsilon_i \end{aligned} \tag{3c}$$

$$\begin{aligned} HOUSEHOLD_i = {} & \beta_0 + \beta_1 AGE_i + \beta_2 AGE_i^2 + \beta_3 FEMALE_i + \beta_4 CONS_i + \beta_5 SOCDEM_i + \beta_6 SEUR_i \\ & + \beta_7 FCOMM_i + \beta_8 EDUC2_i + \beta_9 EDUC3_i + \beta_{10} NOCHILD_i + \beta_{11} CHILD5_i + \varepsilon_i \end{aligned} \tag{3d}$$

$$OTHERCARING_i = \beta_0 + \beta_1 AGE_i + \beta_2 AGE_i^2 + \beta_3 FEMALE_i + \beta_4 CONS_i + \beta_5 SOCDEM_i + \beta_6 SEUR_i + \beta_7 FCOMM_i + \beta_8 EDUC2_i + \beta_9 EDUC3_i + \beta_{10} NOCHILD_i + \beta_{11} CHILD5_i + \varepsilon_i \quad (3e)$$

$$VOLUNTARY_i = \beta_0 + \beta_1 AGE_i + \beta_2 AGE_i^2 + \beta_3 FEMALE_i + \beta_4 CONS_i + \beta_5 SOCDEM_i + \beta_6 SEUR_i + \beta_7 FCOMM_i + \beta_8 EDUC2_i + \beta_9 EDUC3_i + \beta_{10} NOCHILD_i + \beta_{11} CHILD5_i + \varepsilon_i \quad (3f)$$

$$LEISURE_i = \beta_0 + \beta_1 AGE_i + \beta_2 AGE_i^2 + \beta_3 FEMALE_i + \beta_4 CONS_i + \beta_5 SOCDEM_i + \beta_6 SEUR_i + \beta_7 FCOMM_i + \beta_8 EDUC2_i + \beta_9 EDUC3_i + \beta_{10} NOCHILD_i + \beta_{11} CHILD5_i + \varepsilon_i \quad (3g)$$

for $i = 1, 2, \ldots, N$,

where respondent i's time use is modeled as a function of his or her age, age-squared, educational attainment, gender, presence of young children, and welfare state.

This fixed effects model assumes that impacts of cohort and period on time use of sample members are adequately modeled as fixed. This ignores the possibility that the effects of cohort membership and period may have random, as well as, or instead of, fixed effects on time use. This raises the possibility that sample respondents in the same cohort group and / or period may be similar in their time use due to the fact that they share random error components unique to their cohorts or periods of the survey. The standard errors of estimated coefficients of conventional fixed-effects regression models may be underestimated, leading to inflated t-ratios and actual alpha levels that are larger than the nominal .05 or .01 levels.

This heterogeneity problem can be addressed by modifying the fixed effects specification of the general APC regression model toward a random effects model. This implies that we should modify the fixed-effects APC regression model to a mixed effects model. For that purpose, following Yang & Land (2006), we specify a mixed (fixed and random) effects APC regression model, known in the social sciences as multilevel or hierarchical regression model.

4.2 Cross-classified random effects APC model

To specify a hierarchical age-period-cohort (HAPC) regression model, note, that in cross-sectional surveys, such as MTUS, individuals are nested within cells created by the cross-classification of two types of social context: birth cohorts and survey years. That is, respondents are members simultaneously in cohorts and periods. This data structure is displayed in table 3.

Table 3: Two-way cross-classified data structure in MTUS: number of observations in each cohort-by-period cell

	Period									
Cohort	1960-64	1965-69	1970-74	1975-79	1980-84	1985-89	1990-94	1995-99	2000-04	Total
1895-99	887	2	8	0	0	0	0	0	0	897
1900-04	0	96	12	495	0	0	0	0	0	603
1905-09	3128	1668	60	1082	216	0	0	0	0	6154
1910-14	0	1875	85	1201	705	606	0	0	0	4472
1915-19	0	231	529	1496	853	1682	736	0	0	5527
1920-24	0	4144	882	2412	1131	2344	3232	431	0	14576
1925-29	3767	220	867	2577	1067	3038	4073	1668	1421	18698
1930-34	0	5382	971	2464	1247	3234	4193	1787	2968	22246
1935-39	0	2512	1048	2492	1176	3629	4634	1665	3657	20813
1940-44	1451	1722	1073	2681	1581	4009	5759	1826	4124	24226
1945-49	0	70	1255	3397	2005	5017	5692	2478	5050	24964
1950-54	0	0	1043	2841	1855	5588	6573	2786	5931	26617
1955-59	0	0	0	2322	1897	5614	7479	3048	6337	26697
1960-64	0	0	0	418	1504	5019	7312	3156	6789	24198
1965-69	0	0	0	0	942	3465	5777	2785	6767	19736
1970-74	0	0	0	0	0	1518	5666	2348	6503	16035
1975-79	0	0	0	0	0	0	2661	1980	5586	10227
1980-84	0	0	0	0	0	0	0	1610	5322	6932
1985-89	0	0	0	0	0	0	0	0	2252	2252
Total	9233	17922	7833	25878	16179	44763	63787	27568	62707	275870

Each row is a cohort and each column is a period of 5 years. Denote the number of birth cohorts as J and the number of periods as K. The numbers in this J by K matrix are the sample sizes, n_{jk} - the numbers of individuals who belonged to a given birth cohort and were surveyed in a given period. In recognition of the multilevel characteristics of this data structure, we formulate a cross-classified effects APC model to assess the relative importance of the two contexts, cohort, and period, in understanding the individual differences in time use.

In such a model, variability in time use associated with individuals, cohorts, and periods in specified as follows:

Level-1 or “within-cell” model:

$$PAIDWORK_{ijk} = \beta_{0jk} + \beta_1 AGE_{ijk} + \beta_2 AGE^2_{ijk} + \beta_3 FEMALE_{jki} + \beta_4 CONS_{ijk} + \beta_5 SOCDEM_{ijk} + \beta_6 SEUR_{ijk} + \beta_7 FCOMM_{ijk} + \beta_8 EDUC2_{ijk} + \beta_9 EDUC3_{ijk} + \beta_{10} NOCHILD_{ijk} + \beta_{11} CHILD5_{ijk} + e_{jki} \quad (4a)$$

$$EDUCATION_{ijk} = \beta_{0jk} + \beta_1 AGE_{ijk} + \beta_2 AGE^2_{ijk} + \beta_3 FEMALE_{jki} + \beta_4 CONS_{ijk} + \beta_5 SOCDEM_{ijk} + \beta_6 SEUR_{ijk} + \beta_7 FCOMM_{ijk} + \beta_8 EDUC2_{ijk} + \beta_9 EDUC3_{ijk} + \beta_{10} NOCHILD_{ijk} + \beta_{11} CHILD5_{ijk} + e_{jki} \quad (4b)$$

$$CHILDCARE_{ijk} = \beta_{0jk} + \beta_1 AGE_{ijk} + \beta_2 AGE^2_{ijk} + \beta_3 FEMALE_{jki} + \beta_4 CONS_{ijk} + \beta_5 SOCDEM_{ijk} + \beta_6 SEUR_{ijk} + \beta_7 FCOMM_{ijk} + \beta_8 EDUC2_{ijk} + \beta_9 EDUC3_{ijk} + \beta_{10} NOCHILD_{ijk} + \beta_{11} CHILD5_{ijk} + e_{jki} \quad (4c)$$

$$HOUSEHOLD_{ijk} = \beta_{0jk} + \beta_1 AGE_{ijk} + \beta_2 AGE^2_{ijk} + \beta_3 FEMALE_{jki} + \beta_4 CONS_{ijk} + \beta_5 SOCDEM_{ijk} + \beta_6 SEUR_{ijk} + \beta_7 FCOMM_{ijk} + \beta_8 EDUC2_{ijk} + \beta_9 EDUC3_{ijk} + \beta_{10} NOCHILD_{ijk} + \beta_{11} CHILD5_{ijk} + e_{jki} \quad (4d)$$

$$OTHERCARING_{ijk} = \beta_{0jk} + \beta_1 AGE_{ijk} + \beta_2 AGE^2_{ijk} + \beta_3 FEMALE_{jki} + \beta_4 CONS_{ijk} + \beta_5 SOCDEM_{ijk} + \beta_6 SEUR_{ijk} + \beta_7 FCOMM_{ijk} + \beta_8 EDUC2_{ijk} + \beta_9 EDUC3_{ijk} + \beta_{10} NOCHILD_{ijk} + \beta_{11} CHILD5_{ijk} + e_{jki} \quad (4e)$$

$$VOLUNTARY_{ijk} = \beta_{0jk} + \beta_1 AGE_{ijk} + \beta_2 AGE^2_{ijk} + \beta_3 FEMALE_{jki} + \beta_4 CONS_{ijk} + \beta_5 SOCDEM_{ijk} + \beta_6 SEUR_{ijk} + \beta_7 FCOMM_{ijk} + \beta_8 EDUC2_{ijk} + \beta_9 EDUC3_{ijk} + \beta_{10} NOCHILD_{ijk} + \beta_{11} CHILD5_{ijk} + e_{jki} \quad (4f)$$

$$LEISURE_{ijk} = \beta_{0jk} + \beta_1 AGE_{ijk} + \beta_2 AGE^2_{ijk} + \beta_3 FEMALE_{jki} + \beta_4 CONS_{ijk} + \beta_5 SOCDEM_{ijk} + \beta_6 SEUR_{ijk} + \beta_7 FCOMM_{ijk} + \beta_8 EDUC2_{ijk} + \beta_9 EDUC3_{ijk} + \beta_{10} NOCHILD_{ijk} + \beta_{11} CHILD5_{ijk} + e_{jki} \quad (4g)$$

$$e_{ijk} \sim N(0, \sigma^2)$$

Level-2 or "between-cell" model:

$$\beta_{0jk} = \gamma_0 + u_{0j} + v_{0k}, u_{0j} \sim N(0, \tau_u), \quad v_{0k} \sim N(0, \tau_v) \quad (4h)$$

Combined model:

$$PAIDWORK_{ijk} = \gamma_0 + \beta_1 AGE_{ijk} + \beta_2 AGE^2_{ijk} + FEMALE_{ijk} + CONS_{ijk} + SOCDEM_{ijk} + SEUR_{ijk} + FCOMM_{ijk} + EDUC2_{ijk} + EDUC3_{ijk} + NOCHILD_{ijk} + CHILD5_{ijk} + u_{i0} + v_{0k} + e_{ijk} \quad (4i)$$

for $i = 1, 2, ..., n_{jk}$ individuals within cohort j and period k;
$j = 1, \ldots,$ 19 birth cohorts;
$k = 1, \ldots,$ 9 time periods;
where, within each birth cohort j and period k, respondent i's time use is modeled as a function of his or her age, age-squared, educational attainment, gender, presence of young children, and welfare state.

This random-intercepts model specification allows only the level-1 intercept to vary randomly from cohort-to-cohort and period-to-period, but not the level-1 slopes. In this model, β_{0jk} is the intercept or "cell mean" – that is, the mean time use of individuals who belong to birth cohort j and surveyed in period k; $\beta_{1}, \ldots \beta_{11},$ are the level-1 fixed effects; e_{ijk} is the random individual effect – that is, the deviation of individual *ijk*'s score from the cell mean, which are assumed normally distributed with mean 0 and a within-cell variance σ^2; γ_0 is the model intercept, or grand-mean time use of all individuals; u_{0j} is the residual random effect of cohort *j* that is, the contribution of cohort *j* averaged over all periods, on β_{0jk}, assumed normally distributed with mean 0 and variance τ_u ; and v_{0j} is the residual random effect of period *k* – that is, the contribution of period *k* averaged over all cohorts, assumed normally distributed with mean 0 and variance τ_v . In addition, $\beta_{0j} = \gamma_0 + u_{0j}$ is the cohort effect averaged over all periods; and $\beta_{0k} = \gamma_0 + v_{0k}$ is the period effect averaged over all cohorts.

4.3 Results

Tables 4 and 5 report empirical estimates for regression models on the MTUS-data. Table 4 contains baseline ordinary least squares estimates of regression models without controls for period and cohort effects applied to 275870 respondents (equations 3). Estimates of seven regression models, one for each time use category, are given in the table.

Spending time on paid work seems to rise with age as well as spending time on childcare, household and other forms of caring. Growing older negatively affects time spent on education, voluntary work and leisure however. The estimates confirm the assumed nonlinear effect of age. Compatible with prior research, being female is negatively associated with spending time on paid work, and positively with spending time on household work and child care. The estimates of the coefficients for education appear significant as well for most of the time use categories; a higher education relates positively to spending time on paid work, child care, caring for others and voluntary work. For time spent on schooling and training, and on leisure activities, the relation is somewhat less straightforward; people who completed secondary education seem to spend less time on schooling and more time on leisure activities than people who did not complete secondary education. For persons who completed a form of higher education, this relation is opposite. The coefficients for the effect of having (young) children at home are significant for most forms of time use as well; people who do not have young children to care for appear to spend more time on paid work, schooling and training, and leisure activities, and less time on caring activities, and household work than people who have (young) children at home. People who have to care for children of age 5 and older appear to spend more time on paid work, schooling and training and leisure activities than people who have to care for children of age 4 and younger, but less than people who do not have to care for children (anymore). For time spent on childcare, household work and other caring, the effects are similar, but with the opposite sign. People who have to care for children of age 5 or older appear to spend most time on voluntary work as we can see in table 4. Besides these personal characteristics, also the type of welfare state people live in appears crucial when explaining time use variations. People in the former communist welfare states appear to spend most time on paid work, and people in the south European welfare states least compared to the other types. Socio-democratic welfare states seem to stimulate spending time on schooling and training, and conservative welfare states seem to offer a positive environment for spending time on care (both child care and care for acquaintances and relatives) and voluntary work. With respect to time spent on household work, substantial differences can be observed between the welfare states. People in the socio-democratic welfare states seem to spend relatively few hours a day on household work, and people in the south-european and former communistic countries relatively many. Also with respect to time spend on leisure activities substantial differences can be observed; people in the liberal and socio-democratic welfare states seem to spend more time on these activities than people in the conservative, south-european, and former communistic welfare states.

Table 4: Fixed-Effects Regression Models for Various Time Use Categories, MTUS Data, 1960-2004, Without Controls for Period and Cohort Effects

	Dependent						
Independent	Paid work	Education	Childcare	Household	Othercaring	Voluntary	Leisure
Intercept	-89.71*** (3.88)	226.93*** (1.31)	79.47*** (0.84)	-40.00*** (2.13)	5.15*** (1.10)	2.50*** (0.60)	478,35*** (2.82)
Age	20.26*** (0.18)	-10.16*** (0.06)	7.02*** (0.24)	6.26*** (0.10)	0.94*** (0.05)	-0.70* (0,03)	-10.29*** (0.13)
Age^2	-0.27*** (0.002)	0.10*** (0.001)	0.001 (0.000)	-0.45*** (0.001)	-0.005*** (0.001)	0.002*** (0.00)	0.13*** (0.002)
Female	-131.17*** (0.93)	-3.30*** (0.32)	21.39*** (0.20)	144.15*** (0.51)	-12.05*** (0.26)	-1.11*** (0.14)	-39.63*** (0.68)
Cons	3.32*** (1.10)	5.54*** (0.38)	7.02*** (0.24)	6.37*** (0.61)	8.89*** (0.31)	2.49*** (0.17)	-61.24*** (0.80)
Socdem	5.49*** (2.08)	13.71*** (0.71)	3.19*** (0.45)	-12.52*** (1.14)	3.47*** (0.58)	-1.30*** (0.32)	2.92*** (1.51)
Seur	-68.10*** (1.75)	0.53 (0.59)	-2.90*** 0.38)	35.04*** (0.96)	-9.77*** (0.49)	1.39*** (0.27)	-10.34*** (1.27)
Fcomm	53.53*** (1.68)	5.83*** (0.57)	-0.36 (0.36)	16.40*** (0.922)	2.89*** (0.47)	0.87** (0.26)	-89.20*** (1.22)
Educ2	13.95***	-0.81*	2.58***	-14.56***	2.39***	2.80***	1.67*

	(1.10)	(0.37)	(0.24)	(0.60)	(0.31)	(0.17)	(0.80)
Educ3	24.28*** (1.21)	11.81*** (0.41)	7.08*** (0.26)	-21.48*** (0.67)	2.10*** (0.34)	5.70*** (0.19)	-9.26*** (0.88)
Nochild	53.53*** (1.51)	31.38*** (0.48)	-83.65*** (0.31)	-45.54*** (0.78)	-2.39*** (0.40)	0.22 (0.22)	46.98*** (1.03)
Child5	28.51*** (1.51)	24.44*** (0.51)	-58.92*** (0.33)	-18.18*** (0.83)	-0.38 (0.42)	1.86*** (0.23)	27.53*** (1.10)
Adjusted R^2	0.15	0.18	0.27	0.29	0.03	0.007	0.10
AIC	3811125	3214975	2966670	3479721	3107680	2778052	3635020

Note: Standard errors are in parentheses;

*indicates p < 0.05; **indicates p < 0.01; ***indicates p < 0.001, two-tailed test.

Table 5 reports the parameter estimates and for the crossed random effects model (equations 4) estimated on the MTUS data[15]. These results are attained using the restricted maximum-likelihood-empirical Bayes estimated method (Raudenbush and Bryk, 2002). Examining the fit statistics and information criteria at the bottom of the table, it can be seen that the AIC-values of the HAPC-models are lower than the AIC-values of the fixed-effect models (see table 3) which means that the HAPC-models fit the data better. The significant residuals in table 4 indicate that individual differences among the respondents remain after accounting for differences between cohorts and periods. The Intercept parameter is the variance in intercept across cohorts and periods. With a 1-tailed test at $\alpha = 0.05$ there is evidence that intercepts (group means) do vary. These two estimates provide information for calculating the intraclass correlation, which determines the need for a higher level of analysis. The intraclass correlation (ρ) is the measure of differences between groups (cohorts, periods) relative to differences within groups[16]. High values means that the assumption of independence of errors is violated, and a hierarchical analysis is needed to avoid inflated Type I error rate. But, with large samples -as the MTUS sample is- even small values of ρ lead to inflated Type error I (see Tabachnick, 2005). Based on the significant Intercept parameters and the values of ρ, a need for higher order analyses can be seen.

Table 5: HAPC Models for Various Time Use Categories, MTUS Data, 1960-2004: Cross-classified Random Effects

Fixed							

[15] The model estimates in Table 5 were estimated by SPSS PROC mixed.

[16] $\rho = \dfrac{s_{l2}^2}{s_{l1}^2 + s_{l2}^2}$, s_{l1}^2 = level 1 variance (residual), s_{l2}^2 = level 2 variance (intercept)

Effects							
	Paid work	Education	Childcare	Household	Othercaring	Voluntary	Leisure
Intercept	-62.42*** (15.56)	392.15*** (6.46)	75.91*** (2.84)	-66.67*** (6.99)	-18.75*** (14.68)	4.17*** (1.33)	372.25*** (11.39)
Age	17.81*** (0.69)	-17.26*** (0.24)	-0.16 (0.13)	7.36*** (0.33)	1.08*** (0.20)	-0.13* (0.06)	-3.80*** (0.50)
Age^2	-0.23*** (0.01)	0.17*** (0.002)	0.0007 (0.001)	-0.57*** (0.004)	0.002 (0.002)	0.003*** (0.0007)	0.05*** (0.005)
Female	-131.26*** (0.92)	-2.34*** (0.30)	21.06*** (0.19)	144.22*** (0.51)	-12.27*** (0.25)	-1.09*** (0.14)	-40.25*** (0.67)
Cons	-14.85*** (1.38)	4.99*** (0.46)	3.53*** (0.29)	7.06*** (0.76)	4.32*** (0.39)	2.60*** (0.21)	-53.05*** (1.02)
Socdem	14.34*** (2.12)	10.87*** (0.71)	0.42 (0.45)	-11.81*** (1.17)	-0.44 (0.39)	-1.34*** (0.33)	1.33 (1.55)
Seur	-61.09*** (2.27)	1.53* (0.76)	-4.75*** (0.48)	34.62*** (1.23)	-11.39*** (0.64)	1.27*** (0.33)	-26.21*** (1.66)
Fcomm	28.73*** (1.90)	8.00*** (0.63)	-0.18 (0.41)	12.08*** (1.04)	1.84*** (0.54)	1.70*** (0.29)	-74.53*** (1.39)
Educ2	14.64*** (1.11)	5.15*** (0.37)	1.60*** (0.24)	-16.10*** (0.61)	1.36*** (0.31)	2.85*** (0.17)	-0.43 (0.82)
Educ3	29.32*** (1.27)	19.28*** (0.42)	4.26*** (0.27)	-24.81*** (0.70)	0.18*** (0.35)	5.79*** (0.20)	-12.34*** (0.93)
Nochild	61.42*** (1.50)	13.25*** (0.49)	-80.38*** (0.32)	-37.29*** (0.83)	-3.14*** (0.42)	-0.30 (0.23)	49.88*** (1.10)
Child5	33.36*** (1.56)	9.02*** (0.52)	-55.60*** (0.34)	-11.92*** (0.87)	0.08*** (0.44)	1.42*** (0.24)	29.98*** (1.14)
Random Effects[17]							
Intercept	91.02	-63.50	1.94	-6.91	-7.82	-3.24	19.28
Cohort							
1895-1899	45.82	50.14	-17.98	-20.78	18.44	5.31	-66.13
1900-1904	-88.84	73.79	-12.56	22.15	10.14	1.09	-16.12
1905-1909	-55.68	44.59	-10.06	9.18	13.98	4.52	-17.69
1910-1914	-58.18	59.44	-6.12	6.51	9.45	4.13	-24.43
1915-1919	-78.33	67.69	-7.13	7.39	10.23	4.49	-10.54

[17] The parameter estimates of the random effects are estimated using the GLM procedure in SPSS (with period and cohort as factors) on the differences between the residuals of the mixed models and the fixed effects model. This “two-step”procedure is chosen since SPSS cannot compute the parameter estimates of the random effects directly.

1920-1924	-60.39	60.51	-4.51	8.36	10.12	3.40	-18.09
1925-1929	-45.54	62.22	-3.15	-3.76	6.31	2.76	-19.74
1930-1934	-40.85	60.67	-3.98	-0.57	4.99	2.56	-27.63
1935-1939	-48.77	60.18	-1.01	-0.55	3.83	2.63	-24.61
1940-1944	-63.44	62.07	1.03	3.24	3.59	2.59	-19.55
1945-1949	-57.06	62.06	1.02	2.95	4.34	2.83	-25.97
1950-1954	-57.07	67.28	-1.14	1.07	4.86	3.01	-26.97
1955-1959	-60.67	70.55	-5.30	3.02	6.11	2.72	-25.95
1960-1964	-58.61	73.61	-11.08	1.16	7.42	3.28	-24.44
1965-1969	-61.96	72.07	-10.07	3.75	6.72	3.63	-22.66
1970-1974	-71.47	73.06	-3.56	7.89	7.27	3.03	-22.67
1975-1979	-37.21	47.80	0.51	0.31	8.47	3.35	-20.99
1980-1984	-6.39	19.75	3.44	1.86	5.83	3.23	-9.78
1985-1989	0[18]	0	0	0	0	0	0
Period							
1960-1964	-116.97	15.87	12.27	9.96	9.54	-0.71	35.55
1965-1969	-109.70	5.79	2.03	-4.94	2.51	1.44	32.95
1970-1974	-57.18	10.04	3.56	-7.49	14.00	2.79	13.87
1975-1979	-52.72	10.44	8.03	17.68	3.52	0.64	-5.92
1980-1984	-32.77	-10.63	0.80	7.98	3.30	-0.48	-15.38
1985-1989	-29.02	-1.71	1.61	2.69	3.21	0.33	-4.68
1990-1994	-42.46	-1.90	-0.84	11.72	-5.39	0.10	6.04
1995-1999	-25.29	-3.25	1.83	-5.34	9.53	-0.38	7.30
2000-2004	0[19]	0	0	0	0	0	0
AIC	3803450	3193238	2961352	3477470	3105314	2777756	3632507
Covariance parameters							
Residual	56822.10*** (153.03)	6217.19*** (16.74)	2684.85*** (7.23)	17437.84*** (46.96)	4522.00*** (12.18)	1380.75*** (3.72)	30577.11*** (82,35)
Intercept	2537.49*** (387.26)	1278.07*** (185.14)	44.32*** (6.58)	240.47*** (36.30)	316.07*** (77.18)	4.21*** (0.79)	1350.57*** (236.00)
P	0.043	0.17	0.016	0.014	0.065	0.0032	0,042

Note: Standard errors are in parentheses;

*indicates p < 0.05; **indicates p < 0.01; ***indicates p < 0.001, two-tailed test.

[18] This parameter is set to zero because it is redundant.
[19] This parameter is set to zero because it is redundant.

Examining the estimated average effect coefficients for cohorts, it can be seen that the estimated effects on time spent on paid work are particularly positive for the latest birth cohorts, and more negative for the earliest birth cohorts. Also the 1925-1929, 1930-1934, and 1935-1940 birth cohorts spend relatively much time on paid work. With respect to time spent on training and schooling, the various birth cohorts do not seem to differ much with the exception of the latest birth cohorts. The estimated effects on time spent on child care are particularly positive for the 1940-1944 and 1945-1949 cohorts, and the youngest birth cohorts. We also see a positive trend from the oldest birth cohorts to the 1940-1944 and 1945-1949 cohorts, and a negative trend on time spend on child care from the baby boom cohorts to the 1970-1974 cohort. The youngest birth cohorts seem to spend (again) more time on child care. The birth cohorts that appear to spend more time on paid work, spend less hours on household work than the other cohorts. With respect to time spend on care for others, we see a negative trend from the oldest birth cohort to the 1940-1944 cohort, and a positive trend from that cohort to the 1975-1979 birth cohort. The youngest birth cohorts appear to spend less time on care for others. With respect to voluntary work, no clear differences can be observed for the various birth cohorts. Time spent on that activity seem to be relatively constant over the various birth cohorts. Regarding time spent on free time, we see that the estimated effects are particularly positive for the youngest birth cohorts, and negative for the oldest.

Considering the estimated average effect coefficients for periods, a clear negative trend can be observed from the sixties to the most recent years. Apparently, people spend more time on paid work every year since the sixties. An exception forms the 1990-1994 period, likely as a result of the economic recession in that period. Time spent on schooling and training has become less favorite since the sixties as the average effect coefficients for periods show a negative trend. Especially in the period 1980-1984, people seem to spend less time on schooling and training. Since this period was dominated by a recession, this result seems not very unlikely. With respect to time spent on child care table 5 shows particularly positive effects for the earlier periods. Especially in the beginning of the sixties, and at the end of the seventies, people seem to spent more time on child care. During these periods people seem to spend relatively much time on household work as well. Also during the beginning of the eighties and nineties, people spend relatively much time on household work. Considering time spent on care for others, people seem to spend more time on care for others in the beginning of the sixties, the beginning of the seventies, and the end of the nineties than in the other periods. For the 1990-1994 period, the effect on time spent on care for others is particularly negative. The effects on time spent on voluntary work are particularly positive for the late sixties and early seventies. With respect to free time spending, the eighties seem to form a break-point as we see a clear negative trend from the early sixties to the early eighties, and a positive trend onwards.

Examining next the estimated individual-level coefficients in table 5 it can be seen that the qualitative results are quite similar to those given in table 4. The estimated regression coefficients and their standard errors are numerically quite similar between the two tables for the sex, education, and children variables. Estimates for the components of the quadratic age curve are quite different however. For instance, for the linear component of this curve, the estimated coefficient for time spent on child care is reduced from a highly significant 7.02 of table 4 to a nonsignificant -0.16 in table 5, after cohort and time period effects are taken into account. Also for time spent on leisure activities the coefficient for that term is reduced substantially, from -10.29 for the fixed effects model to -3.80 for the HAPC. For time spent on schooling and training the coefficient increased after cohort and period effects are included, from -10.16 to -17.26. The coefficients of the quadratic component of the age curve change also after cohort and period effects are taken into account. For instance for time spent on caring for others, the estimated coefficient increased from a significant -0.005 in table 4 to a nonsignificant 0.002 in table 5. For time spent on leisure activities, the coefficient decreased from 0.13 in table 4 to 0.05 in table 5. Besides the age-effects, also the estimated coefficients for welfare state are quite different for most activities, and change signs for some activities and welfare state types. These findings imply that a failure to control for the effects of cohort and period variation in time use could lead to substantial over- and underestimates of time use variations that are due to aging and also to substantial over- and underestimates of time use variations that are related to the welfare state people participate in.

5. Conclusion

In this paper we have considered the "age-period-cohort conundrum" – the fact that the classical APC model is underidentified due to a linear dependency among age, period, and cohort. We have applied a procedure for mixed regression models to the hierarchical analysis of individual-level data from repeated cross-sections of MTUS, as proposed by Yang and Land (2006a, 2006b). HAPC regression models in the form of cross-classified random effects models have been used to find out whether or not there is significant heterogeneity in time use by cohorts and/or periods.

The HAPC analyses find evidence in support of quadratic age effects on time use. The positive effect of ageing on time spent on paid work decreases during the (individual) life course for instance as well as the negative effect on time spent on schooling and training, and the positive effect on time spent on household work and caring for acquaintances and relatives. Furthermore, the HAPC analyses find evidence in support of the contentions of Liefbroer & Dykstra (2000), and Kronjee (1990) that both cohort and period effects should be distinguished in life course analyses. The circumstances people experience during their "formative phase" appear to determine the time use -and as a result the weighing of activities (and life domains)- during their life course, but historical changes influence cohorts on various moments in the life course and appear to be relevant in the life phases that follow. Finally, the period effects as well as the welfare state effects on time use during the life course seem to show a non-negligible sensitivity for economic circumstances and welfare policies.

References

Anxo, D., J.Y. Boulin, C. Fagan, I. Cebrian, S. Keuzenkamp, U. Klammer, CH. Klenner, G. Moreno and L. Toharia (2006), *Working time options over the life course: new work patterns and company strategies,* European foundation for the improvement of living and working conditions, Dublin: EFILWC.

Becker, H.A. (1992), *Generaties en hun kansen,* Amsterdam: Meulenhoff.

Bovenberg, A.L. (2005), "Balancing work and family life during the life course", *De Economist*, 153: 399-423

Easterlin, R.A. (1980), *Birth and fortune: the impact of numbers on personal welfare,* New York: Basic books.

Fu, W.J. (2000), "Ridge estimator in singular design with application to age-period-cohort analysis of disease rates", *Communications in statistics-theory and method,* 29:263-278.

Glenn, N.D. (1976), "Cohort analysts' futile quest: statistical attempts to separate age, period, and cohort effects", *American sociological review,* 41:900-904.

Glenn, N.D. (2003), “Distinguishing age, period, and cohort effects”, in: J.T. Mortimer and M.J. Shanahan (eds.), *Handbook of the life course,* New York: Kluwer Academic/Plenum, 465-476.

Hagenaars, J.A. (1990), *Categorical longitudinal data: log-linear, panel, trend, and cohort analysis,* Newbury Park:: Sage Publications.

Hobcraft, J., J. Menken, and S. Preston (1982), “Age, period, and cohort effects in demography: a review”, *Population index,* 48:4-43.

Inglehart, R. (1977), *The silent revolution: changing values and political styles among western publics,* Princeton, NJ: Princeton University Press.

Inglehart, R. (1997), *Modernization and postmodernization: cultural, economic and political change in 43 societies,* Princeton, NJ: Princeton University Press.

Klammer, U., S. Keuzenkamp, I. Cebrian, C. Fagan, Ch. Klenner and G. Moreno (2005), *Working time options over the life course: changing social security structures,* European foundation for the improvement of living and working conditions, Dublin: EFILWC.

Kronjee, G.J. (1991), *Veranderingen in levenscyclus, demografische veroudering en collectieve sociale uitgaven,* Utrecht: ISOR/Universiy of Utrecht

Liefbroer, A.C. and P.A. Dykstra (2000), *Levenslopen in verandering,* WRR voorstudies en achtergronden V107, Den Haag: Sdu Uitgevers.

Mulder, C.H. (1993), *Migration dynamics: a life course approach,* dissertation, Amsterdam: Thesis publishers.

Naegele, G., C. Barkholdt, B. de Vroom, J. Goul Andersen and K. Kramer (2003), *A new organisation of time over working life,* European foundation for the improvement of living and working conditions, Dublin: EFILWC.

O’Brien, R.M. (2000), “Age period cohort characteristic models”, *Social science research,* 29: 123-39.

Raudenbush, S.W. and A.S. Bryk (2002), *Hierarchical linear models: applications and daa analysis methods,* Thousand oaks, CA: Sage.

Robertson, C., S. Gandini, and P. Boyle (1999), “Age-Period-Cohort models: a comparative study of available methodologies”, *Journal of clinical epidemiology,* 52:569-583.

Ryder, N.B. (1965), “The cohort as a concept in the study of social change”, *American sociological review,* 30:843-861.

Schmid, G. (2000), “Transitional Labour Markets. A New European Employment Strategy”, in: B. Marin, D. Meulders & D. Snower (eds.), *Innovative Employment Initiatives,* Aldershot, etc.: Ashgate, 223-253.

Schmid, G. and B. Gazier (2002), *The Dynamics of Full Employment: Social Integration Through Transitional Labour Markets,* Cheltenham, UK and Brookfield, US: Edward Elgar.

Tabachnick, B. G. (2005), *Multilevel modeling with SPSS,* workshop presented at Loyola Marymount University, Los Angeles, CA.

Versantvoort, M.C. (2000), *Analysing labour supply in a life course perspective,* dissertation, Amsterdam: Thela thesis.

Wilson, J.A. and W.R. Grove (1999), “The intercohort decline in verbal ability: does it exist?”, *American sociological review”,* 64:253-266.

Yang, Y. and K.C. Land (2006a), “A mixed models approach to the age-period-cohort analysis of repeated cross-section surveys, with an application to data on trends in verbal test scores”, *Sociologcial methodology,* 36:75-97.

Yang, Y. and K.C. Land (2006b), “Age-period-cohort analysis of repeated cross-section surveys; fixed or random effects”, *Sociological methods & research,* 20:1-30.