The endless baby-boomer generation: Cohort differences in participation in political discussions in nine European countries in the period 1976-2008

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1. INTRODUCTION

Political involvement and participation are crucial aspects of social capital development, of civil society and social stability (Putman 1995). In a generational change perspective, we observe in Europe a large gap between 'optimistic' arguments that focus on the intense educational development of younger birth cohorts and 'pessimistic' ones that follow Putnam's ideas of declining participation in civil society and worries about a lack of political involvement and knowledge (Hooghe 2004; Hooghe and Dassonneville 2013; Putnam 2000; Fieldhouse et al. 2007). The young seem to become less involved in politics (Li and Marsh 2008; O'Toole et al. 2003), at least after controlling for education. The first baby-boomers were and remain more active than the "X-generation" and the following ones. Ken Roberts (2012) anticipates the consequences of the 'end of the long baby-boomer generation'. This means notably the emergence of a new generation less politically involved. This 'end' can be seen as paradoxical since the firsts baby-boomers, who are almost at age 70 today, are endlessly very active politically, and continue to have a central role in this domain. In this respect there is no "end" of the baby-boomers' specificity, even if their followers experience the end of a cohort trend of increasing political activism. In France, notably, there has long been observed a decrease in the involvement of the young generations in politics, but the debate focused more on a possible age effect of youth delay in a process of early socialization to politics followed by a catch up effect later in life (Muxel 1991). The implicit idea of such models is that this withdrawal from politics is temporary and followed by further re-investment and commitment in politics. Conversely, other scholars stress on the persistence of characteristics acquired during socialization over the life course (Alwin and Krosnick 1991; Alwin and Krosnick 1991; Dassonneville et al. 2012; Glenn 1980; Jennings and Markus 1984;

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¹ The authors mention a 'moratoire politique', a moratorium in politics that derives from Erik Erikson's (1950, 1955) development stage theory of psychosocial moratorium of the young.

Neundorf et al. 2012; Prior 2010; Sears 1981). After a period of initial socialization and of transition in politics, temporary experiences transform in permanent traits (Bréchon 2011).

Several previous studies already examined changes in political involvement (Blais et al. 2004; Inglehart 1990; Neundorf et al. 2012; Prior 2010; Van den Broek 1996; Van Deth 1990; Van Deth 1991; Van Deth and Elff 2000; Van Deth and Elff 2004). These studies however could not systematize cohort dynamics. Studying change, one can focus on change over the life course (age effects), change over generations (cohort effects) and change over time (period effects) (Firebaugh 1997; Glenn 2005). Period effects happen to all people, regardless of their age and year of birth. A factor that might cause period effects in political participation for example are elections. By age effects one has to think for example of a declining health over time. Cohort effects generally arise during socialization. People seem to be more sensitive to the contextual conditions during the first phase of their lives (Becker 2000).

Our aim here is twofold. At first, important cohort fluctuations in participation in political discussions exist but have not been sufficiently underlined as an important source of change. We make use of recent improvements of the APC methodology to have a better assessment of these cohort-based changes. Thereafter, we search for appropriate explanations for these cohort fluctuations with contextual elements of cohort specific socialization and life conditions.

Our first aim thus is to analyse differences between cohorts. Differences between cohorts are important elements for the understanding of social change (Ryder 1965). As said, many characteristics are established in the first phase of adult life in the context of transition from adolescence to adulthood and thereafter people are much more stable (Alwin and Krosnick 1991; Becker 2000; Dassonneville et al. 2012; Glenn 1980; Jennings and Markus 1984; Neundorf et al. 2012; Prior 2010; Roberts 2012; Sears 1981). Technically this means that differences between cohorts arise by the interaction of period and age effects (Crockett and Voas 2006; Glenn 1980). As a consequence, societal changes occur with the apparition of new cohorts sharing new social characteristics and with the further replacement of older by more recent cohorts (Firebaugh 1992; Inglehart 1977; Inglehart 1990; Mannheim 1952

[1928]; Ryder 1965). Especially political attitudes are known to be very cohort dependent. Dependent on the socialization context, generations develop differential packages of ideas.

Our study is focused on participation in political discussions in Europe. Other scholars have analysed the cohort dynamics of electoral turnout (Wass 2007), electoral volatility (Dassonneville 2012), political interest (Hadjar and Schlapbach 2009), and political leadership (Chauvel 2010), party membership and extra-institutional participation (petition, demonstrations, etc.) in politics (Grasso 2014). Van Deth and Elff found specific cohort patterns for likelihood to frequently discuss politics and likelihood to never discuss politics: participation seems to generally increase over the cohorts (controlled for education and gender and with period on the higher level) but they did not focus on nonlinear cohort fluctuations. As said, our first contribution here is to re-examine findings with respect to differences between cohorts in participation in political discussions with control of age and period effects as they are taken into account by recent age-period-cohort models (Yang and Land 2013). We hereto make use of a new model able to detect cohort nonlinearities pertaining specifically to the cohort variable and that cannot be explained by the simple combination of age and period. This linear/nonlinear question is central in the tradition of cohort analysis (Mason and Wolfinger 2001): "cohort effects" (as well as the age and the period ones) have two dimensions, a linear one and a nonlinear one. The linear dimension expresses for instance the increasing level of living that younger cohorts enjoy, when progressive long term economic growth happens; the non-linear one expresses, when it exists, that some cohorts are specifically above or below the general cohort trend. In France for instance, the cohort born in 1950, is particularly lucky in terms of income (Chauvel and Schroeder 2014), having at the same age a systematic +10% in their income compared to cohorts born 15 years before or after. The contemporary literature on age-period-cohort shows that it is impossible to identify long term trends so that they are unequivocally attributed to period or cohort. Conversely, the cohort "bumps" (the specific empirical divergence of cohorts to the predicted values resulting from the age and period effects they belong to), when they exist, can be clearly identified. Our main interest thus is not the long term linear change that cannot be identified (Firebaugh 1997; Glenn 1989; Glenn 1994; Mason et al. 1973; Yang and Land 2008; Luo 2013). Indeed on the long range, it is empirically equivalent to say that with period change all the population receive 1% more each year versus with cohort change each cohort receives 1% more. A linear growth is not cohort or period specific for APC models. On the contrary, with our method, which adds appropriate constraints, the non-linear changes in these three variables are identifiable in a unique and robust manner. This method focuses on cohort fluctuations and non-linear dynamics where some cohorts are drifting away from the linear trend and others face relapses compared to the cohort linear dynamics. In political participation, cohort bumps or fluctuations of that type have been already detected (Putnam 2000; Becker 2000; Grasso 2014) but our aim is to improve their detection with larger samples and explanation in a comparative perspective.

Our second contribution will include firstly a test of *individual* level explanations for cohort effects. For example level of education could be an important factor in the understanding of changing political behaviour over time (Dalton 1984; Hadjar and Schlapbach 2009). Education can be seen as a major resource for political socialization (Dassonneville et al. 2013; Galston 2004; Hooghe and Dassonneville 2011; Torney-Purta 2002) and obviously level of education strongly varies over cohorts (Smith 1993; Wilson et al. 2011). Results of previous studies show positive effects (Blais et al. 2004; Hadjar and Schlapbach 2009; Nie et al. 1996; Putnam 2000). Although these of course are less likely to explain cohort differences, other explanatory variables we take into account are gender and family structure. We know there are important gender differences in political participation (Blais et al. 2004; Hadjar and Schlapbach 2009; Neundorf et al. 2012; Van Deth and Elff 2004). We take into account marital status as well. Neundorf et al. find (2012) that getting married does not directly affect the degree of political interest while others (Blais et al. 2004; Denver 2008; Stoker and Jennings 1995) hypothesize a positive effect of having a partner. A priori, the degree to which these three factors changed over cohorts and the extent to which these factors actually influence political participation could have an impact on the cohort fluctuations. We secondly try to explain change over birth cohorts with two *contextual* factors that express the specific context of cohort socialization. After all, as said, people are especially susceptible to adopt durable traits while being young. The first contextual factor is the economic situation at the moment a cohort entered the labour market. In comparison to other birth cohorts we take into account, the early baby boom generation entered the labour market in a period of affluence. Affluence is not simply an increase in opportunities and a lower risk of unemployment and poverty, it also develops possibilities of self-expression and need of higher level of fulfilment. This is the general Inglehart (1977) expression of a post-materialist need for political participation. Therefore, we take into account the economic context at age 25. Beyond Inglehart, many authors underline the relation between economic downturns and youth problems pervasively observed (Chauvel and Schröder 2014; Therborn 2014; De Lange *et al.* 2014). The second contextual explanation results from differences between cohorts in relative size. In the Easterlin (1961) tradition, confirmed by Easterlin et al. (1993), the larger a birth cohort, the stronger its risk to face scarcity of employment, poverty, and social problems resulting from population overcrowding. This could be true in economics but could be less appropriate in political terms where numbers and social density count: the 'protest generation' is as well a large generation, benefitting in social morphologic terms (Durkheim 1964 [1893]) from a larger 'social volume' and 'moral density' that increase interdependence, opportunities for integration, and ultimately communication. From this perspective it could be expected that the larger a cohort, the stronger its opportunities of collective mobilization and of political discussion of its own interest.

2. DATA AND MEASUREMENTS

We use the *Mannheim Eurobarometer Trend File* (Schmitt and Scholz 2005) which contains 78 surveys and which ends in 2002. We added *Eurobarometer* surveys conducted until the end of 2008. Nine countries (presented in the graphs under their International standard organisation ISO code) are selected on the base of their seniority in the survey: France (fr), Belgium (be), Netherlands (nl), West Germany (de), Italy (it), Luxembourg (lu), Denmark (dk), Ireland (ie) and Great Britain (uk). We remove people who are younger than 20 and people who are older than 69 at the moment of interview from the data. After this deletion the number of respondents is between sixty and seventy thousand for all countries except Luxembourg (which has almost 30,000 respondents).

People are asked 'When you get together with friends, would you say you discuss political matters frequently, occasionally, or never?'. Since it is impossible to say how often 'frequently' and 'occasionally' exactly are, we decide to contrast the people who answered 'never' to the others.²

We measure education by age at which people left school. We construct the following three categories and include them as dummies: people who left school before reaching the age of seventeen, people who left school while being seventeen, eighteen or nineteen years old, and people who left school while being at least twenty years old. Since we only include people aged 20+, this third group also includes the ones who are still studying. We also use dummy variables for sex (reference is male), and marital status (single/divorced/separated/widowed=0, married/cohabiting=1).

Economic situation in the period of labour market entrance is measured by the detrended relative value of the logged gross domestic product per capita in real terms (constant purchasing power parity dollars 1995) when the cohort is 25 years old. The source is the Penn world tables version 7.1.

Cohort size is obtained from the World Health Organisation Mortality database that provides the size of the different cohorts of the countries which are the base of the calculations of the populations at risk by age groups. We take into account the detrended relative size of the birth cohort in the resident population.

Figure 1 and 2 are based on all available information for the period 1976-2008. In order to make it possible to compare our APC models with and without controls, we based these models on the same groups of people. This means that in the models without controls we do not take into account people

² Additional analyses in which the frequently discussers are contrasted to the occasionally and never

discussers show similar results. We estimated the same models with a continuous dependent variable

as well. The best solution would be to make use of an ordinal logistic regression specification, but due

to the limitations in the general linear model glm with constrains in Stata we did not have this

opportunity.

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with missing values on at least one of the controls. This deletion reduces the number of cases by about seven per cent.

3. METHODS

The method we apply here is the APCD (Age Period Cohort - Detrended) model that is designed to disentangle the effects of age, period and cohort.³ This model is a modernization of a former one developed by Holford (1983): both are designed to retrieve nonlinear cohort coefficients. There, the cohort effect reflects the divergence from the linear trend and retains a cohort curvature expressing the specificity of some cohorts compared to others. The aim of the APCD is to detect cohort bumps expressing the additional information brought by birth cohort to the model with only age and period (Chauvel 2013, Chancel 2014, Chauvel and Schröder 2014). It detects and measures the intensity of the deviation from the linear cohort trend. Compared to the former Holford propositions, this one accepts control variables, can handle a large variety of specifications, and provides confidence intervals of estimators, statistical tests and criteria able to help in the cohort diagnosis.

We generalize here a former OLS type APC model (Chauvel and Schröder 2014) in a logit one. For each country, we consider a dependent variable y_i^{apc} that denotes the existence (0/1) of participation in political discussions for individual i of age a, in period p and then belonging to cohort c = p - a. Categorical time effect variables pertaining to age effects α_a , period effects π_p , and cohort effects γ_c , are then indexed by age a, period p and cohort c. To provide accurate controls at the individual level, we consider j covariates $x_{i,j}$ (which can be continuous or binary). Including appropriate constraints, the APCD model with the following expression has a unique and identifiable solution:

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³ The APCD is available as a Stata ado-file. It can be downloaded by typing 'ssc install apcd' in Stata.

$$\begin{cases} logitPr\big(y_i^{apc}=1\big) = \alpha_a + \pi_p + \gamma_c + \alpha_0 rescale(a) + \gamma_0 rescale(c) + \beta_0 + \sum_j \beta_j x_{i,j} + \varepsilon_i \\ \sum_a \alpha_a = \sum_p \pi_p = \sum_c \gamma_c = 0 \\ slope_a(\alpha_a) = slope_p(\pi_p) = slope_c(\gamma_c) = 0 \\ with \ p = c + a \ and \ restricted \ to \ c_{min} < c < c_{max} \end{cases}$$

(APCD)

 β_0 is the constant, we consider j control variables $x_{i,j}$ related to β_j coefficients, α_a is the age effect vector indexed by age group a, π_p is the period vector and γ_c is the cohort vector. These vectors exclusively reflect the *non-linear* effect of age, period and cohort, as we assign two sets of constraints: each vector sums up to zero and has a slope of zero. These vectors are null when the age, period or cohort effects are linear. The terms α_0 Rescale(a) and γ_0 Rescale(c) absorb the linear trends; Rescale is a transformation that standardizes the coefficients α_0 and γ_0 : it transforms age from the initial code a_{min} to a_{max} to the interval -1 to +1. Since the first and last cohorts appear just once in the model (the oldest age group of the first period and the youngest of the last), their coefficients are less stable; we therefore exclude them. This model is thus an expression of the traditional Mason and Smith (1985) APC model, including controls, having a logit specification and following the Holford (1983) idea that cohort is detrended in the sense that constraints impose zero slopes on age, period and cohort α_a π_p and γ_c coefficients, while linear trends are absorbed by α_0 Rescale(a) and γ_0 Rescale(c). A comparison of the results between the APCD model without and then with control variables (for instance education, marital status, etc.) delivers a diagnosis on the degree to which cohort effects are the consequence of changes in population characteristics or not (see results on Appendix 1).

The detrended cohort effect coefficients γ_c are zero when cohort effects are absent. In this case, cohorts do not deviate from age and period characteristics; then the APCD model provides no improvement compared to a simple age and period model (AP) with first and last cohorts omitted, which consists of:

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⁴ The constraint Slope_a(α_a)=0 means the trend of the age effect is zero and is true only if Σ_a [(2a - a_{min} - a_{max}) α_a] = 0. This constraint is easily expressed as a linear equation of coefficients.

$$\begin{cases} logitPr\big(y_i^{ap}=1\big) = \alpha_a + \pi_p + \alpha_0 rescale(a) + \pi_0 rescale(p) + \beta_0 + \sum_j \beta_j x_{i,j} + \varepsilon_i \\ \sum_a \alpha_a = \sum_p \pi_p = 0 \\ slope_a(\alpha_a) = slope_p(\pi_p) = 0 \\ restricted \ to \ c_{min} < c < c_{max} \end{cases}$$

(AP)

If at least one γ_c coefficient is significantly different from zero however, then a simple AP model is insufficient. In this case, some cohorts are above or below the expected trend resulting from the simple addition of age and period dynamics. Thus to retain appropriate parsimonious models, comparing the Raftery's (1986) BIC of the (AP) and of the (APCD) is a diagnosis on the relevance of nonlinear cohort effects (Appendix 2).

Other APC techniques converge to similar results. In Appendix 3 we present results of more usual models: the Hierarchic APC (HAPC) developed by Yang and Land (2008) and the APC-IE intrinsic estimator model (Yang et al 2008). They converge in the shape, intensity and significance to the similar results and confirm our strategy. This APCD technique has an additional interesting property: since for all the countries we have a slope-zero baseline for cohort dynamics comparison, cohort bumps (the nonlinear component we focus on here) are easily comparable. We propose then a post-APCD analysis: we will run a linear OLS regression with the detrended cohort coefficients (derived from the APCD-model with controls) as dependent variable and the detrended relative size of the birth cohort in the resident population and detrended relative value of the logged GDP (gross domestic product) per capita in real terms (constant purchasing power parity dollars 1995) when the cohort is 25 year old as independent variables. For 12 cohorts in 9 countries we dispose of these three factors from 1950 (for cohort 1925-'29) to 2009 (cohort 1980-'84). We then retain cohorts born from 1925-'29 to 1980-'84.

4. RESULTS

Next to the APC-analyses, more descriptive ways of analysing the cohort effect provide important

insights. Since the APCD models are designed to detect nonlinear cohort effects, it is important to first

describe the actual trends.

Bivariately, in all countries, we see a positive effect of year of birth until the cohorts born around 1950

and then a decline in participation in political discussion. In some countries the effect of year of birth

is stagnant for the people born after 1950, and in other countries we see a negative effect. There thus is

a peak in political discussion for those born in the late 1940 or early 1950.

Next we analyse effects of age, period and cohorts visually. To this end, we present a "synthetic

cohort" figure and a "cohort diagram". To smooth the changes, we use 10 year groupings of periods

and cohorts. Synthetic cohort figures make it possible to see differences between birth cohorts given

certain periods. In order to compare people with different years of birth but with similar ages, one

should look at different points on the lines. The synthetic cohort figure thus shows the developments

in political participation for different birth cohorts over the survey years. Cohort diagrams make it

possible to see differences between birth cohorts given certain ages. So, what does the age group 20-29

look like in case they are born between 1950 and 1959, what does it look like in case they are born

between 1960 and 1969, etc. To follow people belonging to a certain cohort over the years, one has to

move the eyes only up and down.

[Figure 1 about here]

[Figure 2 about here]

In the synthetic cohort figure, the cohorts born in the 1940s and 1950s are higher in the political

participation indicator while older and younger cohorts are less active in political discussions. These

⁵ This "synthetic cohort" tool is a common descriptive method in demography, sociology and epidemiology (Mason and Fienberg 1985; Preston et al. 2001). The horizontal axis represents age and the vertical one a dependent variable (such as intensity of political participation). Curves represent the trajectory of birth cohort groups, so we can observe the differences in aging process. The cohort diagram is an alternative where cohort is on the horizontal axis, and the curves present age groups, so we can compare different cohorts when they have

the same age.

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changes give some sense to Becker's typology of generations retained by Van den Broek (1996) and then reworked by Van Deth and Elff (2004): the 'pre-war generation' (born before 1930), 'silent generation' (from birth cohort 1931 to 1940), 'protest generation' (born between 1941 to 1955), 'lost generation' (born from 1956 to 1970) and 'pragmatic generation' (born after 1970). These typologies have been precised and systematized by Grasso (2014:66). For our purpose, these typologies are too much detailed since 'pre-war' and 'silent' generations are in a continuous dynamic structure before the top, and the 'lost' and 'pragmatic' arrive after when the slope is negative. In general, we observe nonlinear continuities, such as bumps, more than strong ruptures. In our nine countries, the 'protest generation' reached a top in political participation and the following ones experienced a relapse. This relapse is rather surprising since we know these cohorts are more educated than the previous ones and since education is known to positively influence political participation.

The synthetic cohort graph confirms as well that the level of participation in political discussion of a cohort is relatively stable and the cohort relative rankings are generally stable over time. 'The stable relative position versus other birth cohorts', as Van den Broek (1996) puts is, can be seen. Not the absolute but the relative position on a variable is characteristic of a cohort. The cohort diagram shows the cohort to cohort dynamics where the cohorts born after 1950 are stagnating or even declining in political discussion at a given age. Two other elements appear: in terms of period effects, from the 1980s to the 1990s, all birth cohorts experience an increase in their political involvement. This period effect could result either of the context of the 1980s that was less propitious for political involvement, or of the political revival of the 1990s where the fall of the wall and the opening of a new era of development of Europe could have given more room and matter for political discussions. In the cohort diagram we see an age effect as well: until the age of 50-59, political involvement generally increases. These two graphs confirm that the cohorts of young adults in the 1960s and 1970s have always been specifically active. In a theory of socialisation related to Karl Mannheim (1952 [1928]), these cohorts who benefitted from a specific period of political socialisation such as May 1968 in France, or the context of the sixties in the western world (Mead 1070) benefitted from better opportunities of political socialisation.

Now we turn to our APCD-methods so that we can get to know more about the significances of the cohort effects, so that we can take into account control variables, and so that we can identify the nonlinearities in the three time variables (age, period, and cohort). We first discuss the effects of the control variables and then look to the cohort diagnosis.

In all countries we see the same picture: the highest educated people are most likely to discuss politics and the lowest educated are least likely. In all countries the differences between educational categories are significant at p<0.001. The largest differences between the two extreme educational groups can be seen in Luxembourg followed by Great Britain and the smallest difference can be seen in Denmark followed by West-Germany. In every country the gender gap is in the same direction, with men being more likely to discuss politics than women, with significant gaps at p<0.001. The gender gap is largest in Italy followed by West-Germany and smallest in the Netherlands followed by Great Britain. The case of marital status is more ambiguous. In six of our nine countries (Belgium, Netherlands, West-Germany, Luxembourg, Ireland, Great Britain) there appears to be a significant difference between those living with partner (married and cohabiting people) and the others who are less participative. The difference between both groups is largest in West-Germany and smallest in Great Britain. For participation in political discussions, level of education apparently is the most important explanatory variable.

Now we turn to the degree to which people born in different years differ in terms of frequence of political discussion. The figures show the cohort effects with the confidence intervals. As said, the deviation of the cohorts from the linear trends is shown.

[Figure 3 about here]

In all countries we detect similar bumps: the middle birth cohorts pertaining to the early baby boom generation are furthest above the linear trend everywhere. This is in line with what we saw in figures 1 and 2. Anyway, the APCD method is able to provide deeper insights. First, the descriptive method of figure 1 and 2 is acceptable for the European level sample, but the collapse by country give less

obvious results due to smaller samples. Second, The model delivers by-country non-linear trajectories with their confidence intervals so that we can compare the shapes and make the difference between flatter countries such as Denmark or Germany and more bumpy ones such as France or Netherlands. Third, we can include controls for relevant variables (at first education but also demographic characteristics) that could *a priori* explain the fluctuations. The model is able to confirm the intrinsic specificity of birth cohorts in terms of political participation.

The APCD results confirm that in most countries the cohort of 1945 is most politically participative. In Belgium and Germany the cohort of 1950 is most participative and in Italy the cohorts of 1950/1955. In Luxembourg the difference between the most and least participative cohorts is largest. Note that the confidence intervals are also much larger due to the relatively small sample size in this country. The cohort of 1945 is 0.30 above the linear trend and the cohort of 1915 is 0.40 below the linear trend. In France, the difference between the most and least participative cohorts is large as well. Also here the cohorts of 1915 and 1945 are respectively the least and most likely to participate in political discussions. The accompanying coefficients are -0.33 and 0.31. The bumps are relatively small in the Netherlands and especially in Denmark. In Denmark the coefficients of the two extreme cohorts are -0.19 and 0.23.

Although in all countries the middle cohorts are most politically active, the shapes of the lines are not completely similar. In some countries it is really one cohort that stands out (for example in the case of Great Britain) while in other countries there are multiple cohorts that stand out to the same degree (for example in the case of West-Germany). In most countries political participation continuously rises over the cohorts until the most politically active cohort and thereafter continuously declines over the cohorts.

We tested whether there are similarities in shapes in order to build a typology. Clustering tools such as the Ward CAH however are unable to detect specific types of countries. Apparently there are no real types but a continuum of shapes without obvious contrasts between groups of countries. Controlling for level of education, marital status and gender hardly changes the cohort effects. The shapes of the continuous and dotted lines in figure 3 are very similar. This means that the composition of the different birth cohorts in terms of education, gender ratio or family structure is not the source of the bump of the early baby boom generation. In other words, the cohort nonlinearities in political discussions do not derive from individual characteristics (even in terms of education) but from other sources, such as cohort specific contexts.

Now we turn to the other two explanatory factors.

[Table 1 about here]

We provide a post estimation regression of the cohort APCD coefficients found in the model with control variables. A set of 9 countries times 12 cohorts coefficients (108 cells) regressed on cohort size and on economic situation at age 25 appears to provide a good explanation of the bumps we observe for the early baby boomer cohorts (see Appendix 4 for details). The two explanatory variables play a significant role in the cohort differences in political participation. The explanation resulting from cohort size seems strongest, but with a sign opposed to the one Easterlin should have anticipated: large cohorts are more politically active. Then large cohorts experiencing better economic situations at the entry in the labour market, as it is the case of the early baby boom generation in many European countries, might benefit from better political socialization. Conversely, relatively smaller cohorts, victims of economic recession, risk a decline in political participation.

5. CONCLUSION AND DISCUSSION

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⁶ The height of the variance inflation factor (1.19) shows that the model does not suffer from multicollinearity.

This paper described and explained differences between birth cohorts in participation in political discussions in France, Belgium, Netherlands, Germany, Italy, Luxembourg, Denmark, Ireland and Great Britain in the period 1980-2006. Using descriptive and new APC methods, we found clear differences between cohorts in political participation. In general people born around 1950, the early baby boom generation, are most likely to discuss politics and the farther away a birth cohort from this peak year, the less politically participative. This picture is very similar in the different European countries of our set. Although the shapes and effect sizes differ a little bit over the nine countries, people born between 1945 and 1955 are everywhere on the top of a wave of stronger participation in political discussions. Apparently, the early baby boom generation is not only special with respect to health and labour market success (Becker 2000; Buchholz et al. 2009; Roberts 2012), they are also special with respect to political participation.

With respect to the individual level variables we make use of, we see that they cannot explain the cohort bumps: higher education is not the explanation of the specificity of the early baby boomers even if in all countries education matters strongly for participation in political discussions. We also find men to be more likely to discuss politics in all countries. Marital status plays a less obvious role. In six of the nine countries there is a significant effect in which the married and cohabiting people participate more. Taking into account these three independent variables does almost not change the shape of the cohort effects.

Explanations for cohort differences that appear to be useful are cohort size and economic situation at the time of entry into adulthood. In comparison to older and younger cohorts, members of the early baby boom generation matured in a period of strong welfare states (Roberts 2012), rapid economic growth and increasing affluence (Van den Broek 1996). They started their professional lives in times of labour market upgrading and in times of full employment and had a low risk of youth unemployment as a consequence. Older and younger cohorts entered the labour market in a context of scarcity or economic slowdown that could come with stronger relative frustration, more competition within the cohort and less opportunities for solidarity and political commitment in universities, businesses and in the civil society sphere. These cohorts are characterized as well by a smaller relative

size, which diminishes their potential political impact. This result converges with the Kahn and Mason (1987) critique of the Easterlin 'political alienation effect': cohort crowding is not associated with a decline in political participation, but with an increase. This means that the Easterlin argument could be complex: the cohort crowding impairs the economic context of a large cohort but at the same time this size gives more room for efficient mobilisation. The worst case is the one of small cohorts entering adult life in a period of economic slowdown, which is precisely the case of the cohorts born before 1925 and of those born after 1965.

Further research must invest more this mystery of the clear over-involvement of the early baby boomers in politics, and complete the demographic and economic explanation we propose here. Next to financial security, another important factor for example could be existential security. Because they were born just after World War II, baby boomers experienced much more existential security than older cohorts who faced the European crisis and war in childhood and early adulthood. According to the theory of Inglehart (1977), this existential security could make people more politically active. Future research is also encouraged to test whether changing patterns of media consumption can explain cohort differences. Media is important because consumption changed strongly over time (Glenn 1994; Knulst and Kraaykamp 1998; Samuel 1996) and because discussing politics without having some information about it is hardly possible and ultimately, all political information we have comes from media sources. With a R-square of 0.29 there is room for other explanations, but the fact that many European countries affect similar shapes with a convergence of explanation show an interesting example of how social generations can be influenced by the context of their socialization. Fifty years after Ryder's (1965) seminal paper, cohort analyses continue to offer useful insights. One of these results is the importance of cohort effects where the 'political moratorium of the young' is not an age effect that is absorbed with aging but a cohort effect that could affect the participation of the post 1950s birth cohorts forever.

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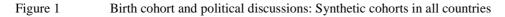
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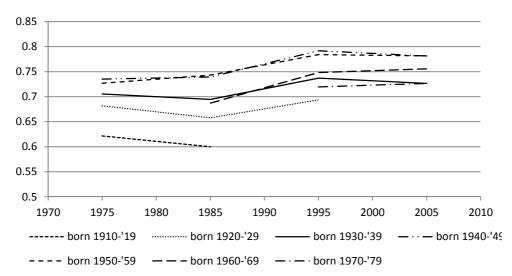
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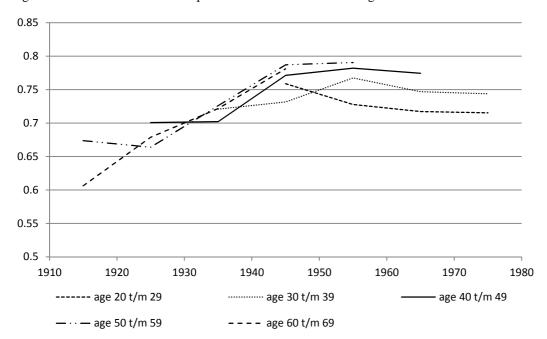




Y-axis: proportion of people that says to occasionally or frequently discuss politics (instead of never); X-axis: periods in decades; lines are birth cohort groups

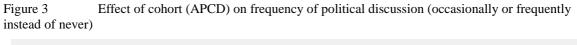
Source: Eurobarometer 1976-2008, countries included: FR/BE/NL/DE/IT/LU/DK/IE/GB, N=535,883

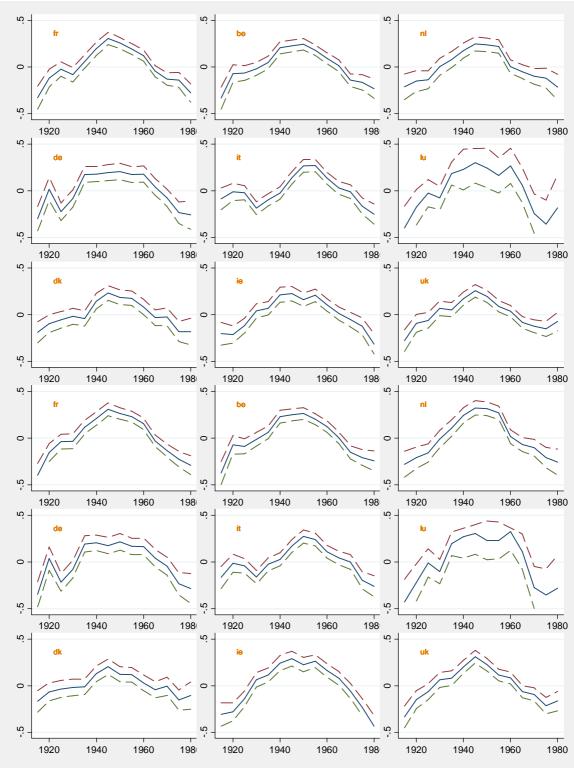
Figure 2 Birth cohort and political discussions: Cohort diagram in all countries



Y-axis: proportion of people that says to occasionally or frequently discuss politics (instead of never); X-axis: birth cohorts in decades; lines are age groups

Source: Eurobarometer 1976-2008, countries included: FR/BE/NL/DE/IT/LU/DK/IE/GB, N=535,883





Full lines: estimates, dashed lines; Grey lines: confidence intervals

Above: without controls, below: with controls of level of education, sex, and marital status.

Source: Eurobarometer 1980-2006

Table 1 Linear OLS regression of cohort effects found in the APCD-model with controls by detrended economic situation at age 25 and relative detrended demographic size of the cohort

-	Coef.		Robust SE
Cohort size	.581	***	.127
GDP	.505	**	.188
Constant	.000		.014

^{*} p<0.050, ** p<0.010, *** p<0.001, N=108

Appendix 1 - Logistic APCD models on frequency of political discussion (occasionally or frequently instead of never) (source: Eurobarometer 1980-2006) without/with controls

APCD without controls

	fr:b	fr:se	be:b	be:se	nl:b	nl:se	de:b	de:se	it:b	it:se	lu:b	lu:se	dk:b	dk:se	ie:b	ie:se	uk:b	uk:se
Cohort 1915	-0.328	0.064	-0.333	0.060	-0.209	0.070	-0.299	0.066	-0.086	0.059	-0.398	0.119	-0.189	0.058	-0.204	0.062	-0.280	0.059
Cohort 1920	-0.118	0.048	-0.071	0.049	-0.149	0.057	0.018	0.063	-0.011	0.048	-0.176	0.097	-0.096	0.048	-0.214	0.047	-0.092	0.049
Cohort 1925	-0.021	0.040	-0.063	0.040	-0.136	0.049	-0.223	0.048	-0.021	0.038	-0.025	0.075	-0.055	0.045	-0.118	0.041	-0.061	0.042
Cohort 1930	-0.082	0.039	-0.018	0.036	0.003	0.046	-0.083	0.047	-0.186	0.035	-0.076	0.063	-0.017	0.044	0.040	0.039	0.067	0.041
Cohort 1935	0.061	0.037	0.051	0.034	0.080	0.044	0.175	0.043	-0.096	0.034	0.185	0.063	-0.042	0.041	0.069	0.037	0.052	0.039
Cohort 1940	0.196	0.037	0.206	0.033	0.177	0.041	0.179	0.041	-0.023	0.034	0.229	0.111	0.144	0.043	0.212	0.041	0.172	0.035
Cohort 1945	0.306	0.034	0.227	0.032	0.249	0.039	0.196	0.044	0.140	0.034	0.302	0.112	0.232	0.041	0.224	0.039	0.255	0.034
Cohort 1950	0.257	0.031	0.245	0.031	0.238	0.036	0.207	0.044	0.267	0.035	0.245	0.109	0.186	0.040	0.160	0.037	0.195	0.033
Cohort 1955	0.194	0.029	0.180	0.029	0.221	0.036	0.174	0.043	0.270	0.033	0.164	0.096	0.175	0.039	0.207	0.034	0.090	0.031
Cohort 1960	0.122	0.030	0.095	0.030	0.005	0.036	0.180	0.044	0.136	0.033	0.269	0.096	0.082	0.042	0.104	0.035	0.036	0.031
Cohort 1965	-0.044	0.030	0.017	0.031	-0.049	0.037	0.041	0.046	0.031	0.035	0.060	0.095	-0.033	0.043	0.012	0.036	-0.083	0.032
Cohort 1970	-0.127	0.033	-0.140	0.035	-0.099	0.043	-0.074	0.047	-0.009	0.037	-0.244	0.108	-0.024	0.048	-0.053	0.039	-0.124	0.034
Cohort 1975	-0.138	0.041	-0.163	0.041	-0.118	0.054	-0.233	0.059	-0.163	0.044	-0.356	0.131	-0.181	0.054	-0.126	0.045	-0.153	0.042
Cohort 1980	-0.278	0.050	-0.232	0.052	-0.214	0.070	-0.258	0.078	-0.250	0.056	-0.180	0.180	-0.182	0.072	-0.316	0.055	-0.075	0.051
Age 20	-0.043	0.025	-0.057	0.025	-0.085	0.032	-0.092	0.038	-0.136	0.027	-0.096	0.067	-0.093	0.034	-0.106	0.027	-0.164	0.026
Age 25	0.001	0.024	-0.021	0.024	-0.009	0.030	0.002	0.035	0.027	0.027	0.027	0.060	-0.044	0.032	-0.075	0.027	-0.007	0.026
Age 30	-0.024	0.025	0.005	0.026	0.026	0.030	-0.031	0.036	-0.027	0.029	-0.069	0.069	0.035	0.033	0.063	0.028	0.102	0.026
Age 35	0.050	0.027	-0.005	0.027	0.097	0.032	0.012	0.038	0.056	0.030	0.030	0.078	0.008	0.035	0.014	0.032	0.025	0.028
Age 40	0.018	0.031	0.012	0.029	-0.013	0.034	0.026	0.039	0.008	0.030	0.159	0.093	0.130	0.039	0.150	0.037	0.069	0.031
Age 45	0.018	0.032	0.098	0.029	0.019	0.037	0.110	0.042	0.087	0.031	0.149	0.098	0.078	0.039	0.077	0.036	0.046	0.032
Age 50	0.037	0.032	0.084	0.030	0.029	0.039	0.115	0.040	0.107	0.031	-0.078	0.103	0.035	0.039	0.025	0.038	-0.002	0.034
Age 55	-0.030	0.032	0.015	0.029	-0.027	0.037	0.005	0.040	0.092	0.030	-0.068	0.097	-0.088	0.038	-0.049	0.038	0.080	0.033
Age 60	0.034	0.032	-0.060	0.029	0.026	0.036	0.035	0.037	-0.039	0.030	-0.065	0.093	0.010	0.035	-0.012	0.036	-0.020	0.031
Age 65	-0.061	0.030	-0.072	0.030	-0.064	0.038	-0.182	0.036	-0.176	0.030	0.011	0.094	-0.070	0.037	-0.088	0.033	-0.130	0.031
Period 1975	0.187	0.021	-0.061	0.020	0.081	0.025	-0.126	0.027	0.205	0.021	0.063	0.043	0.028	0.024	-0.063	0.021	-0.071	0.023
Period 1980	-0.103	0.023	-0.030	0.022	0.111	0.027	0.086	0.030	-0.212	0.021	0.068	0.043	-0.132	0.025	0.083	0.023	-0.020	0.024
Period 1985	-0.080	0.022	0.030	0.022	0.026	0.027	0.077	0.033	-0.357	0.023	-0.189	0.042	0.003	0.027	0.023	0.023	0.064	0.024
Period 1990	-0.120	0.021	0.098	0.021	-0.120	0.026	0.164	0.030	0.103	0.023	0.067	0.042	0.180	0.028	0.027	0.022	0.236	0.022
Period 1995	0.098	0.024	0.148	0.022	-0.292	0.026	-0.189	0.029	0.405	0.026	-0.106	0.040	-0.016	0.029	-0.125	0.023	-0.135	0.023
Period 2000	-0.121	0.023	-0.193	0.022	-0.205	0.028	-0.089	0.030	0.137	0.025	0.049	0.044	-0.026	0.030	0.040	0.024	-0.167	0.023
Period 2005	0.139	0.023	0.009	0.021	0.398	0.029	0.079	0.031	-0.281	0.023	0.048	0.056	-0.036	0.031	0.015	0.025	0.094	0.023
Rescacoh	0.582	0.053	1.295	0.050	0.981	0.066	0.739	0.069	1.374	0.052	-0.004	0.122	1.178	0.064	-0.012	0.056	-0.241	0.055
Rescaage	0.194	0.030	0.559	0.028	0.385	0.036	0.252	0.039	0.468	0.030	-0.053	0.077	0.409	0.037	0.137	0.034	0.018	0.031
Constant	0.740	0.012	0.397	0.011	1.391	0.015	1.604	0.015	0.835	0.012	0.986	0.025	1.386	0.014	0.514	0.012	0.738	0.012

APCD with controls: education (reference = tertiary education), gender (reference = male), marital status (reference = widower, divorced, bachelor with no partner, etc)

	fr:b	fr:se	be:b	be:se	nl:b	nl:se	de:b	de:se	it:b	it:se	lu:b	lu:se	dk:b	dk:se	ie:b	ie:se	uk:b	uk:se
Cohort 1915	-0.398	0.065	-0.373	0.063	-0.278	0.071	-0.347	0.068	-0.166	0.061	-0.427	0.124	-0.167	0.059	-0.308	0.063	-0.333	0.059
Cohort 1920	-0.153	0.049	-0.071	0.050	-0.209	0.059	0.036	0.064	-0.014	0.049	-0.220	0.101	-0.065	0.049	-0.280	0.049	-0.150	0.049
Cohort 1925	-0.036	0.041	-0.087	0.041	-0.157	0.050	-0.215	0.049	-0.043	0.039	-0.011	0.078	-0.034	0.046	-0.139	0.042	-0.063	0.043
Cohort 1930	-0.032	0.040	-0.011	0.037	-0.009	0.047	-0.078	0.048	-0.161	0.037	-0.101	0.066	-0.018	0.045	0.063	0.040	0.063	0.041
Cohort 1935	0.119	0.037	0.064	0.035	0.109	0.045	0.194	0.044	-0.026	0.035	0.195	0.065	-0.011	0.042	0.116	0.038	0.082	0.039
Cohort 1940	0.212	0.038	0.230	0.035	0.246	0.042	0.206	0.042	0.028	0.036	0.271	0.118	0.128	0.044	0.244	0.042	0.202	0.036
Cohort 1945	0.309	0.035	0.250	0.033	0.325	0.039	0.176	0.045	0.171	0.035	0.305	0.114	0.204	0.042	0.290	0.041	0.311	0.035
Cohort 1950	0.265	0.032	0.264	0.033	0.316	0.037	0.217	0.046	0.273	0.036	0.231	0.106	0.123	0.041	0.227	0.039	0.224	0.034
Cohort 1955	0.231	0.030	0.203	0.029	0.272	0.037	0.167	0.045	0.240	0.035	0.231	0.100	0.118	0.040	0.263	0.035	0.115	0.032
Cohort 1960	0.154	0.031	0.125	0.031	0.017	0.037	0.166	0.046	0.109	0.035	0.325	0.101	0.031	0.043	0.165	0.036	0.083	0.032
Cohort 1965	-0.028	0.032	0.005	0.032	-0.067	0.038	0.041	0.048	0.044	0.037	0.110	0.097	-0.044	0.044	0.080	0.037	-0.064	0.033
Cohort 1970	-0.132	0.035	-0.151	0.036	-0.100	0.044	-0.046	0.049	0.001	0.040	-0.274	0.115	-0.006	0.049	-0.056	0.041	-0.093	0.036
Cohort 1975	-0.224	0.042	-0.207	0.043	-0.207	0.055	-0.234	0.061	-0.196	0.046	-0.352	0.141	-0.154	0.055	-0.232	0.048	-0.213	0.045
Cohort 1980	-0.289	0.052	-0.241	0.054	-0.257	0.072	-0.283	0.081	-0.261	0.058	-0.282	0.184	-0.105	0.074	-0.433	0.059	-0.164	0.053
Age 20	-0.042	0.026	-0.037	0.026	-0.070	0.033	-0.023	0.040	-0.185	0.030	-0.071	0.078	-0.089	0.035	-0.087	0.030	-0.135	0.027
Age 25	0.004	0.025	-0.017	0.025	0.001	0.030	0.022	0.036	0.017	0.028	0.056	0.062	-0.048	0.033	-0.042	0.028	0.006	0.027
Age 30	-0.028	0.026	0.001	0.027	0.024	0.031	-0.036	0.037	-0.002	0.031	-0.051	0.075	0.031	0.034	0.068	0.029	0.099	0.027
Age 35	0.040	0.028	-0.013	0.029	0.080	0.033	-0.030	0.040	0.082	0.031	-0.005	0.084	0.018	0.036	-0.015	0.033	0.020	0.029
Age 40	0.026	0.031	0.014	0.030	-0.025	0.035	-0.016	0.040	0.063	0.032	0.095	0.094	0.123	0.040	0.124	0.038	0.037	0.032
Age 45	0.033	0.033	0.073	0.031	0.015	0.038	0.066	0.043	0.087	0.033	0.119	0.103	0.078	0.040	0.041	0.038	0.017	0.033
Age 50	0.016	0.032	0.064	0.032	0.012	0.039	0.070	0.041	0.106	0.033	-0.072	0.107	0.031	0.040	0.008	0.039	-0.021	0.035
Age 55	-0.018	0.032	0.014	0.030	-0.009	0.037	0.002	0.041	0.081	0.031	-0.049	0.095	-0.078	0.039	-0.035	0.039	0.092	0.033
Age 60	0.033	0.032	-0.049	0.030	0.020	0.036	0.061	0.038	-0.091	0.031	-0.049	0.095	-0.004	0.036	-0.001	0.038	-0.025	0.031
Age 65	-0.063	0.031	-0.051	0.031	-0.049	0.039	-0.116	0.037	-0.158	0.031	0.029	0.103	-0.062	0.038	-0.061	0.034	-0.091	0.031
Period 1975	0.163	0.021	-0.060	0.020	0.116	0.025	-0.137	0.028	0.209	0.022	0.085	0.045	0.012	0.024	-0.071	0.022	-0.063	0.024
Period 1980	-0.076	0.023	-0.004	0.023	0.084	0.028	0.085	0.031	-0.210	0.022	0.069	0.045	-0.058	0.025	0.100	0.023	-0.022	0.024
Period 1985	-0.086	0.023	0.006	0.023	-0.034	0.027	0.073	0.034	-0.351	0.024	-0.213	0.044	0.025	0.028	0.015	0.023	0.041	0.024
Period 1990	-0.117	0.022	0.060	0.022	-0.097	0.027	0.211	0.031	0.104	0.024	0.079	0.044	0.084	0.029	0.023	0.023	0.246	0.023
Period 1995	0.107	0.024	0.179	0.023	-0.271	0.027	-0.210	0.030	0.390	0.027	-0.125	0.042	-0.061	0.029	-0.120	0.024	-0.147	0.024
Period 2000	-0.119	0.023	-0.177	0.022	-0.146	0.029		0.031	0.106	0.026	0.014	0.046	-0.016	0.031	0.031	0.025	-0.121	0.023
Period 2005	0.128	0.023	-0.003	0.022	0.348	0.030	0.083	0.032	-0.249	0.024	0.092	0.058	0.013	0.031	0.020	0.026	0.066	0.024
Rescacoh	0.002	0.056	0.756	0.053	0.419	0.069	0.413	0.072	0.856	0.056	-0.533	0.135	0.065	0.073	-0.481	0.060	-0.648	0.057
Rescaage	0.217	0.030	0.573	0.029	0.369	0.037	0.249	0.040	0.521	0.032	-0.049	0.079	-0.004	0.040	0.136	0.035	0.012	0.032
Education (high=ref)																		
Middle	-0.731	0.028	-0.763	0.026	-0.752	0.033	-0.665	0.049	-0.494	0.035	-0.794	0.118	-0.566	0.036	-0.836	0.045	-0.745	0.042
Low	-1.364	0.029	-1.330	0.028	-1.262	0.033	-1.221	0.046	-1.295	0.032	-1.495	0.115	-1.035	0.033	-1.445	0.046	-1.481	0.037
Sex	-0.555				-0.199			0.028					-0.514				-0.513	
Married/cohabiting (other=ref)	0.028			0.023	0.125		0.307	0.029	-0.010					0.030		0.028		0.024
Constant	1.832	0.030	1.403	0.028	2.128	0.034	2.857	0.049	2.250	0.035	2.144		2.141	0.035	1.913	0.046	2.124	0.040
	1.002	3.000	255	3.020	0	3.054	2.007	3.0 13	50	3.000		3.110	/_	3.033	2.010	3.0 10		3.0 10

Appendix 2 – A BIC comparison of models

	(A)	(AP)	(APC)	Saturated
fr	74350.8	74172.9	74033.4	74417.1
be	77463.2	76528.7	<u>76433.9</u>	76826.3
nl	60008.3	59632.8	<u>59590.8</u>	59977.8
de	51134.6	50890.7	50903.3	51287.7
it	74586.2	72782.4	<u>72674.7</u>	73055.9
lu	28755.5	28777.0	<u>28746.5</u>	29101.4
dk	56965.7	<u>56374.0</u>	56378.4	56771.4
ie	73884.2	73886.6	73803.7	74191.0
uk	73053.7	72753.2	<u>72723.9</u>	73109.8

Here we compare the BIC of several models to detect the most parsimonious solutions. The lowest BIC, provided that the gap exceeds 4 units, denotes the best models. Age alone (A) and the full-interactions saturated models are never relevant. In most of the case, the introduction of cohort effects improves the model, exception with Germany and Denmark where age and period effects (AP) with no cohort bumps are sufficient.

Appendix 3 – Results provided by APC-IE and by HAPC (both are in Logit specification and with no control variables)

A3-a Detailed results provided by APC-IE

```
***************
Intrinsic estimator of APC effects
                                                  No. of obs
                                                                      60018
                                                 Residual df = 59988

Scale parameter = 1

(1/df) Deviance = 1.22915
Optimization : ML
Deviance
            = /3/3-._=
= 60026.05033
                = 73734.25257
                                                  (1/df) Pearson = 1.000634
Pearson
Variance function: V(u) = u*(1-u/1)
                                                  [Binomial]
Link function : g(u) = \ln(u/(1-u))
                                                 [Logit]
                                                  AIC
                                                                  = 1.229535
Log likelihood = -36867.12629
                                                  BIC
                              OIM
    poldisc
                  Coef. Std. Err.
                                         z P> |z|
                                                        [95% Conf. Interval]

    age_20
    .0836665
    .0259449
    3.22
    0.001
    .0328154

    age_25
    .0607936
    .0242976
    2.50
    0.012
    .0131713

    age_30
    .0013341
    .0246278
    0.05
    0.957
    -.0469355

                                                                   .1345176
                                                                     .108416
                .0645524
                           .0262045
                                                                     .1159122
     age_35
                                        2.46
                                               0.014
                                                        .0131925
                                               0.900 -.0523716
                                       0.13
                          .0285434
      age_40 |
                .0035724
                                                                     .0595165
                                               0.732
                                                                    .0485696
      age_45 |
               -.0102651 .0300183
                                       -0.34
                                                        -.0690999
      age_50
               -.0230529
                           .0298542
                                       -0.77
                                               0.440
                                                        -.0815661
                                                                     .0354604
     age_55
               -.0557764 .0305415
                                     -1.83 0.068 -.1156366
                          .0317621
                                                                   .0386034
-.0399871
     age_60
               -.0236493
                                                        -.0859019
                                       -0.74
                                               0.457
                                       -3.24
               -.1011753
                                                       -.1623635
      age_65
                            .031219
                                               0.001
period_1975
               .0215393 .0230552
                                       0.93
                                               0.350
                                                        -.023648
                                                                    .0667267
               -.2172181
                           .0226112
                                                        -.2615353
period_1980
                                       -9.61
                                               0.000
                                                                     -.172901
                                       -7.95
period_1985
               -.1678575
                          .0211101
                                               0.000
                                                        -.2092325
                                                                   -.1264825
              -.1189308
                          .0202563
                                               0.000
                                                      -.1586323
                                                                  -.0792292
                                       -5.87
period_1990 |
                                                                    .2113657
                           .0220899
                .1680702
                                                         .1247748
 period_1995 |
                                       7.61
                                               0.000
period_2000
              -.0070358
                          .0222891
                                       -0.32
                                               0.752 -.0507216
                                                                       .03665
 period_2005
               .3214327
                           .0294653
                                       10.91
                                               0.000
                                                        .2636818
                                                                     .3791836
                                                      -.4519204
                          .0739061
cohort_1910
               -.3070672
                                       -4.15
                                               0.000
                                                                     -.162214
               -.2573226
                                              0.000
                                                        -.378723 -.1359222
 cohort_1915 |
                          .0619401
                                       -4.15
                .01/2828 .0465767 .0207306 .03047
               -.0472828
                                       -1.02
 cohort_1920 |
                                               0.310
                                                        -.1385715
                                       0.54
                                                                     .0960227
 cohort_1925
                            .038415
                                               0.589
                                                        -.0545615
                          .0376355
                                       -1.86
2.22
                                                       -.1437706
                                                                     .0037579
               -.0700064
 cohort_1930
                                               0.063
                           .035665
                .0790986
 cohort_1935
                                               0.027
                                                        .0091964
                                                                     .1490008
                                                       .1483145
               .2176169
                                       6.15
                                                                     .2869193
 cohort_1940
                            .035359
                                               0.000
                .3199873
                                               0.000
                                                         .2553537
 cohort_1945
                           .0329769
                                        9.70
                .3005908
                           .0304001
                                                         .2410077
                                                                     .3601739
cohort_1950
                                       9.89
                                               0.000
                           .0286108
                                                        .1759648
                .2320409
                                                                    .2881171
 cohort_1955
                                       8.11
4.83
                                               0.000
                           .0291167
 cohort_1960 |
                .1406133
                                               0.000
                                                         .0835456
                                                                      .197681
               -.0326316 .0293364 -1.11 0.266 -.0901299
 cohort_1965
                                                                   .0248667
                                       -2.35 0.019 -.13867 -.0126424
-3.22 0.001 -.204004 -.0495207
 cohort_1970
               -.0756562
                           .0321505
               -.1267623 .0394097
cohort_1975
 cohort_1980 |
                                                                   -.1722261
                                      -5.40
-1.18
                                               0.000 -.3682149
               -.2702205 .0499981
                                     54.65 0.000 6934CT
 cohort_1985
               -.1237288
                           .1047338
                                                                     .0815457
      _cons | .7192615 .0131617
                                                        .6934651
                                                  = 57959
Aesidual df = 57929
Scale parameter = (1/df) Deviance
Intrinsic estimator of APC effects
Optimization : ML
              = 76116.3476
Deviance
                = 57959.20281
                                                  (1/df) Pearson = 1.000521
Variance function: V(u) = u*(1-u/1)
                                                  [Binomial]
Link function : g(u) = \ln(u/(1-u))
                                                  [Logit]
                                                        = 1.314314 
 = -559219.4 
                                                  AIC
Log likelihood = -38058.1738
```

BIC

144	gf	OIM	_	Ds. _	[05% Game	T
poldisc	Coef.	Std. Err.	Z 	P> z 	[95% Conf.	Interval]
age_20	.0419832	.0255799	1.64	0.101	0081526	.0921189
age_25	.0580859	.0249167	2.33	0.020	.00925	.1069218
age_30	.0360728	.0255271	1.41	0.158	0139594	.086105
age_35	.0062803	.0260899	0.24	0.810	0448549	.0574155
age_40	.0149087	.0265704 .0274762	0.56 2.82	0.575	0371682 .0235581	.0669857 .1312627
age_45 age_50	.0774104 .0455509	.0282575	1.61	0.005 0.107	0098327	.1312627
age_55	0622407	.0285234	-2.18	0.029	1181455	0063359
age_60	0928704	.0290337	-3.20	0.001	1497753	0359655
age_65	1251811	.0306363	-4.09	0.000	1852272	0651351
period_1975	4569215	.0229593	-19.90	0.000	5019209	4119221
period_1980	3263217	.0218845	-14.91	0.000	3692146	2834289
period_1985	1216135	.0200645	-6.06	0.000	1609391	0822879
period_1990	.104236 .2850264	.0196837 .0214205	5.30 13.31	0.000	.0656566 .2430429	.1428154
period_1995 period_2000	.1044205	.0214205	4.81	0.000	.0618367	.1470043
period_2005	.4111738	.0277733	14.80	0.000	.3567391	.4656086
cohort_1910	3240639	.0808322	-4.01	0.000	482492	1656358
cohort_1915	3514488	.0605278	-5.81	0.000	4700811	2328164
cohort_1920	0599638	.0456108	-1.31	0.189	1493594	.0294318
cohort_1925	0466806	.0387466	-1.20	0.228	1226225	.0292614
cohort_1930	0213487	.0356953	-0.60	0.550	0913102	.0486129
cohort_1935	.0768616	.0337699	2.28	0.023	.0106738	.1430494
cohort_1940 cohort_1945	.2248252 .2828252	.0322932 .0316414	6.96 8.94	0.000	.1615317 .2208091	.2881186 .3448412
cohort_1950	.2833726	.0310414	9.23	0.000	.2231686	.3435765
cohort_1955	.2323197	.0278016	8.36	0.000	.1778295	.2868099
cohort_1960	.1355158	.0283264	4.78	0.000	.0799971	.1910345
cohort_1965	.0750402	.0292803	2.56	0.010	.017652	.1324285
cohort_1970	0930637	.0329467	-2.82	0.005	157638	0284893
cohort_1975	0986988	.0398249	-2.48	0.013	1767543	0206434
cohort_1980	1964392	.0516103	-3.81	0.000	2975935	0952849
cohort_1985 _cons	1190529 .339625	.1068518 .0133079	-1.11 25.52	0.265 0.000	3284785 .3135419	.0903727 .365708
	.339023				.3133419	
*******	******	******	******	*****		
******************	******	******	*****	*****		
nl			*****			
nl Intrinsic est:	imator of APC		*****	No.	of obs =	
nl			*****	No. Resi	dual df =	60256
nl Intrinsic est: Optimization	imator of APC : ML	effects	*****	No. Resi Scal	dual df = e parameter =	60256 1
nl Intrinsic est:	imator of APC	effects 95952	****	No. Resi Scal (1/d	dual df =	60256 1 .9837022
nl Intrinsic est: Optimization Deviance	imator of APC : ML = 59273.9	effects 95952	*****	No. Resi Scal (1/d	dual df = e parameter = f) Deviance =	60256 1 .9837022
nl Intrinsic est: Optimization Deviance	imator of APC : ML = 59273.9 = 60300.6	effects 95952 59232	******	No. Resi Scal (1/d (1/d	<pre>dual df = e parameter = f) Deviance = f) Pearson = omial]</pre>	60256 1 .9837022
nl Intrinsic est: Optimization Deviance Pearson	imator of APC : ML = 59273.9 = 60300.6	effects 95952 59232	******	No. Resi Scal (1/d	<pre>dual df = e parameter = f) Deviance = f) Pearson = omial]</pre>	60256 1 .9837022
nl Intrinsic est: Optimization Deviance Pearson Variance funct	imator of APC : ML = 59273.9 = 60300.6	effects 95952 59232 u*(1-u/1)	******	No. Resi Scal (1/d (1/d [Bin [Log	<pre>dual df = e parameter = f) Deviance = f) Pearson = omial] it]</pre>	60256 1 .9837022 1.000742
Intrinsic est: Optimization Deviance Pearson Variance funct Link function	imator of APC : ML = 59273.9 = 60300.6 :ion: V(u) = u : g(u) = 1	effects 95952 59232 u*(1-u/1) ln(u/(1-u))	******	No. Resi Scal (1/d (1/d	<pre>dual df = e parameter = f) Deviance = f) Pearson = omial] it] =</pre>	60256 1 .9837022 1.000742
nl Intrinsic est: Optimization Deviance Pearson Variance funct	imator of APC : ML = 59273.9 = 60300.6 :ion: V(u) = u : g(u) = 1	effects 95952 59232 u*(1-u/1) ln(u/(1-u))	******	No. Resi Scal (1/d (1/d [Bin [Log	<pre>dual df = e parameter = f) Deviance = f) Pearson = omial] it] =</pre>	60256 1 .9837022 1.000742
Intrinsic est: Optimization Deviance Pearson Variance funct Link function	imator of APC : ML = 59273.9 = 60300.6 :ion: V(u) = u : g(u) = 1	effects 95952 59232 u*(1-u/1) ln(u/(1-u))	*******	No. Resi Scal (1/d (1/d [Bin [Log	<pre>dual df = e parameter = f) Deviance = f) Pearson = omial] it] =</pre>	60256 1 .9837022 1.000742
Intrinsic est: Optimization Deviance Pearson Variance funct Link function Log likelihood	imator of APC : ML = 59273.9 = 60300.6 :ion: V(u) = u : g(u) = 1	effects 95952 59232 u*(1-u/1) ln(u/(1-u)) 97976		No. Resi Scal (1/d (1/d [Bin [Log AIC BIC	<pre>dual df = e parameter = f) Deviance = f) Pearson = omial] it] = =</pre>	60256 1.9837022 1.000742 .9842079 -603955.1
Intrinsic est: Optimization Deviance Pearson Variance funct Link function	imator of APC : ML = 59273.9 = 60300.6 :ion: V(u) = u : g(u) = 1	effects 95952 59232 u*(1-u/1) ln(u/(1-u))	******* Z	No. Resi Scal (1/d (1/d [Bin [Log	<pre>dual df = e parameter = f) Deviance = f) Pearson = omial] it] =</pre>	60256 1.9837022 1.000742 .9842079 -603955.1
Intrinsic est: Optimization Deviance Pearson Variance funct Link function Log likelihood poldisc	imator of APC : ML = 59273.9 = 60300.6 ion: V(u) = u : g(u) = 1	effects 95952 59232 1*(1-u/1) ln(u/(1-u)) 97976 OIM Std. Err.	Z	No. Resi Scal (1/d (1/d [Bin [Log AIC BIC	<pre>dual df = e parameter = f) Deviance = f) Pearson = omial] it] = = [95% Conf.</pre>	60256 1 .9837022 1.000742 .9842079 -603955.1
Intrinsic est: Optimization Deviance Pearson Variance funct Link function Log likelihood	imator of APC : ML = 59273.9 = 60300.6 :ion: V(u) = u : g(u) = 1	effects 95952 59232 u*(1-u/1) ln(u/(1-u)) 97976		No. Resi Scal (1/d (1/d [Bin [Log AIC BIC	<pre>dual df = e parameter = f) Deviance = f) Pearson = omial] it] = =</pre>	60256 1.9837022 1.000742 .9842079 -603955.1
Intrinsic est: Optimization Deviance Pearson Variance funct Link function Log likelihood poldisc age_20	imator of APC : ML = 59273.9 = 60300.6 ion: V(u) = u : g(u) = 1 d = -29636.9 Coef.	effects 95952 69232 1*(1-u/1) ln(u/(1-u)) 97976 OIM Std. Err. .0322063	z 	No. Resi Scal (1/d (1/d [Bin [Log AIC BIC P> z	<pre>dual df = e parameter = f) Deviance = f) Pearson = omial] it] = [95% Conf</pre>	60256 1.9837022 1.000742 .9842079 -603955.1
Intrinsic est: Optimization Deviance Pearson Variance funct Link function Log likelihood poldisc poldisc age_20 age_25 age_30 age_35	imator of APC : ML = 59273.9 = 60300.6 cion: V(u) = u : g(u) = 1 d = -29636.9 Coef0260843 .0603317 .0575739 .1240404	effects 95952 69232 a*(1-u/1) ln(u/(1-u)) 97976 OIM Std. Err. .0322063 .0293075 .0285336 .029659	-0.81 2.06 2.02 4.18	No. Resi Scal (1/d (1/d [Bin [Log AIC BIC 0.418 0.040 0.044 0.000	<pre>dual df = e parameter = f) Deviance = f) Pearson = omial] it] = [95% Conf0892075 .0028902 .0016491 .0659098</pre>	60256 1.9837022 1.000742 .9842079 -603955.1 Interval] .0370389 .1177733 .1134987 .1821709
Intrinsic est: Optimization Deviance Pearson Variance funct Link function Log likelihood poldisc poldisc age_20 age_25 age_30 age_35 age_40	imator of APC : ML = 59273.9 = 60300.6 cion: V(u) = u : g(u) = 1 d = -29636.9 Coef. -0260843 .0603317 .0575739 .1240404 -0099002	effects 95952 69232 u*(1-u/1) ln(u/(1-u)) 97976 OIM Std. Err. .0322063 .0293075 .0285336 .029659 .0311933	z -0.81 2.06 2.02 4.18 -0.32	No. Resi Scal (1/d (1/d [Bin [Log AIC BIC 0.418 0.040 0.044 0.000 0.751	<pre>dual df = e parameter = f) Deviance = f) Pearson = omial] it] = [95% Conf0892075 .0028902 .0016491 .0659098071038</pre>	60256 1.9837022 1.000742 .9842079 -603955.1 Interval] .0370389 .1177733 .1134987 .1821709 .0512376
Intrinsic est: Optimization Deviance Pearson Variance funct Link function Log likelihood poldisc age_20 age_25 age_30 age_35 age_40 age_45	imator of APC : ML = 59273.9 = 60300.6 cion: V(u) = u : g(u) = 1 d = -29636.9 Coef. -0260843 .0603317 .0575739 .1240404 -0099002 -0101401	effects 05952 69232 1*(1-u/1) ln(u/(1-u)) 07976 OIM Std. Err0322063 .0293075 .0285336 .029659 .0311933 .0337837	z 	No. Resi Scal (1/d (1/d [Bin [Log AIC BIC 0.418 0.040 0.044 0.000 0.751 0.764	<pre>dual df = e parameter = f) Deviance = f) Pearson = omial] it] = [95% Conf0892075 .0028902 .0016491 .06590980710380763549</pre>	60256 1.9837022 1.000742 .9842079 -603955.1 Interval] .0370389 .1177733 .1134987 .1821709 .0512376 .0560747
Intrinsic est: Optimization Deviance Pearson Variance funct Link function Log likelihood poldisc age_20 age_25 age_30 age_35 age_40 age_45 age_50	imator of APC : ML = 59273.9 = 60300.6 cion: V(u) = u : g(u) = 1 d = -29636.9 Coef0260843 .0603317 .0575739 .1240404009900201014010123911	effects 05952 69232 1*(1-u/1) ln(u/(1-u)) 07976 OIM Std. Err. .0322063 .0293075 .0285336 .029659 .0311933 .0337837 .0353675	z -0.81 2.06 2.02 4.18 -0.32 -0.30 -0.35	No. Resi Scal (1/d (1/d [Bin [Log AIC BIC 0.418 0.040 0.044 0.000 0.751 0.764 0.726	<pre>dual df = e parameter = f) Deviance = f) Pearson = omial] it] = [95% Conf0892075 .0028902 .0016491 .065909807103807635490817101</pre>	60256 1.9837022 1.000742 .9842079 -603955.1 Interval] .0370389 .1177733 .1134987 .1821709 .0512376 .0560747 .0569279
Intrinsic est: Optimization Deviance Pearson Variance funct Link function Log likelihood poldisc poldisc age_20 age_25 age_30 age_35 age_40 age_45 age_50 age_55	imator of APC : ML = 59273.9 = 60300.6 ion: V(u) = u : g(u) = 1 d = -29636.9 Coef260843 .0603317 .0575739 .12404040099002010140101239110747186	effects 95952 59232 a*(1-u/1) ln(u/(1-u)) 97976 OIM Std. Err. .0322063 .0293075 .0285336 .029659 .0311933 .0337837 .0353675 .035058	z -0.81 2.06 2.02 4.18 -0.32 -0.30 -0.35 -2.13	No. Resi Scal (1/d (1/d [Bin [Log AIC BIC P> z 0.418 0.040 0.044 0.000 0.751 0.764 0.726 0.033	dual df = e parameter = f) Deviance = f) Pearson = omial] it] =	60256 1.9837022 1.000742 .9842079 -603955.1 Interval]0370389 .1177733 .1134987 .1821709 .0512376 .0560747 .05692790060063
Intrinsic est: Optimization Deviance Pearson Variance funct Link function Log likelihood	imator of APC : ML = 59273.9 = 60300.6 ion: V(u) = 1 : g(u) = 1 d = -29636.9 Coef0260843 .0603317 .0575739 .124040400990020101401012391107471860383146	effects 95952 59232 1*(1-u/1) ln(u/(1-u)) 97976 OIM Std. Err. .0322063 .0293075 .0285336 .029659 .0311933 .0337837 .035058 .035058	-0.81 2.06 2.02 4.18 -0.32 -0.30 -0.35 -2.13 -1.09	No. Resi Scal (1/d (1/d [Bin [Log AIC BIC P> z 0.418 0.040 0.044 0.000 0.751 0.764 0.726 0.033 0.277	dual df = e parameter = f) Deviance = f) Pearson = omial] it] = =	60256 1.9837022 1.000742 .9842079 -603955.1 Interval] .0370389 .1177733 .1134987 .1821709 .0512376 .0560747 .0569279 -0060063 .0308364
Intrinsic est: Optimization Deviance Pearson Variance funct Link function Log likelihood poldisc poldisc age_20 age_25 age_30 age_35 age_40 age_45 age_50 age_55	imator of APC : ML = 59273.9 = 60300.6 ion: V(u) = u : g(u) = 1 d = -29636.9 Coef260843 .0603317 .0575739 .12404040099002010140101239110747186	effects 95952 59232 a*(1-u/1) ln(u/(1-u)) 97976 OIM Std. Err. .0322063 .0293075 .0285336 .029659 .0311933 .0337837 .0353675 .035058	z -0.81 2.06 2.02 4.18 -0.32 -0.30 -0.35 -2.13	No. Resi Scal (1/d (1/d [Bin [Log AIC BIC P> z 0.418 0.040 0.044 0.000 0.751 0.764 0.726 0.033	dual df = e parameter = f) Deviance = f) Pearson = omial] it] =	60256 1.9837022 1.000742 .9842079 -603955.1 Interval]0370389 .1177733 .1134987 .1821709 .0512376 .0560747 .05692790060063
Intrinsic est: Optimization Deviance Pearson Variance funct Link function Log likelihood	imator of APC : ML = 59273.9 = 60300.6 ion: V(u) = u : g(u) = 1 d = -29636.9 Coef0260843 .0603317 .0575739 .1240404009900201014010123911074718603831460703971	effects 95952 59232 1*(1-u/1) ln(u/(1-u)) 97976 OIM Std. Err. 0322063 .0293075 .0285336 .029659 .0311933 .0337837 .0353675 .035058 .035058 .0352818 .0383311	-0.81 2.06 2.02 4.18 -0.32 -0.35 -2.13 -1.09 -1.84 -9.83 -3.47	No. Resi Scal (1/d (1/d [Bin [Log AIC BIC 0.418 0.040 0.044 0.000 0.751 0.764 0.726 0.033 0.277 0.066	dual df = e parameter = f) Deviance = f) Pearson = omial] it] = = [95% Conf	60256
Intrinsic est: Optimization Deviance Pearson Variance funct Link function Log likelihood poldisc poldisc age_20 age_25 age_30 age_35 age_40 age_45 age_50 age_55 age_60 age_65 period_1975 period_1980 period_1985	imator of APC : ML = 59273.9 = 60300.6 ion: V(u) = u : g(u) = 1 d = -29636.9 Coef. 0260843 .0603317 .0575739 .124040400990020101401012391107471803831460703971262881309137520901374	effects 25952 269232 1*(1-u/1) 1n(u/(1-u)) 27976 OIM Std. Err0322063 .0293075 .0285336 .029659 .0311933 .0337837 .0353675 .035058 .0352818 .0383311 .0267339 .0262969 .0246239	z -0.81 2.06 2.02 4.18 -0.32 -0.35 -2.13 -1.09 -1.84 -9.83 -3.47 -3.66	No. Resi Scal (1/d (1/d [Bin [Log AIC BIC P> z 0.418 0.040 0.044 0.000 0.751 0.764 0.726 0.033 0.277 0.066 0.000 0.001 0.000	dual df = e parameter = f) Deviance = f) Pearson = omial it = =	60256
Intrinsic est: Optimization Deviance Pearson Variance funct Link function Log likelihood poldisc poldisc age_20 age_25 age_30 age_35 age_40 age_45 age_50 age_55 age_60 age_65 period_1975 period_1980 period_1985 period_1990	imator of APC : ML = 59273.9 = 60300.6 cion: V(u) = u : g(u) = 1 d = -29636.9 Coef. -0260843 .0603317 .0575739 .1240404 -0099002 -0101401 -0123911 -0747186 -0383146 -0703971 -2628813 -0913752 -0901374 -0908206	effects 05952 69232 1*(1-u/1) ln(u/(1-u)) 07976 OIM Std. Err0322063 .0293075 .0285336 .029659 .0311933 .0337837 .0353675 .035088 .0352818 .0352818 .0383311 .0267339 .0262969 .0246239 .023684	z -0.81 2.06 2.02 4.18 -0.32 -0.30 -0.35 -2.13 -1.09 -1.84 -9.83 -3.47 -3.66 -3.83	No. Resi Scal (1/d (1/d [Bin [Log AIC BIC P> z 0.418 0.040 0.044 0.000 0.751 0.764 0.726 0.033 0.277 0.066 0.033 0.277 0.066 0.000 0.001 0.000 0.000	dual df = e parameter = f) Deviance = f) Pearson = omial] it] = [95% Conf0.892075 .0028902 .0016491 .065909807103807635490817101143431107465614552473152787142916213839931372404	60256
Intrinsic est: Optimization Deviance Pearson Variance funct Link function Log likelihood	imator of APC : ML = 59273.9 = 60300.6 ion: V(u) = u : g(u) = 1 d = -29636.9 Coef. 0260843 .0603317 .0575739 .12404040099002010140101239110747186038314607039712628813091375209013740908206168557	effects 95952 59232 1*(1-u/1) ln(u/(1-u)) 97976 OIM Std. Err0322063 .0293075 .0285336 .029659 .0311933 .0337837 .0353675 .035058 .035058 .035058 .035058 .035058 .0363311 .0267339 .0262969 .0246239 .023684 .0240877	z -0.81 2.06 2.02 4.18 -0.32 -0.30 -0.35 -2.13 -1.09 -1.84 -9.83 -3.47 -3.66 -3.83 -7.00	No. Resi Scal (1/d (1/d [Bin [Log AIC BIC P> z 0.418 0.040 0.044 0.000 0.751 0.764 0.726 0.033 0.277 0.066 0.000 0.001 0.000 0.000 0.000	dual df = e parameter = f) Deviance = f) Pearson = omial it = =	60256
Intrinsic est: Optimization Deviance Pearson Variance funct Link function Log likelihood	imator of APC : ML = 59273.9 = 60300.6 ion: V(u) = u : g(u) = 1 d = -29636.9 Coef	effects 95952 59232 1*(1-u/1) ln(u/(1-u)) 97976 OIM Std. Err. 0322063 0293075 0285336 029659 0311933 0337837 035058 035058 035058 0352818 0383311 0267339 0262969 0246239 023684 0240877 0259291	z -0.81 2.06 2.02 4.18 -0.32 -0.35 -2.13 -1.09 -1.84 -9.83 -3.47 -3.66 -3.83 -7.00 -0.76	No. Resi Scal (1/d (1/d [Bin [Log AIC BIC P> z 0.418 0.040 0.044 0.000 0.751 0.764 0.726 0.033 0.277 0.066 0.000 0.001 0.000 0.001 0.000 0.000 0.000 0.446	dual df = e parameter = f) Deviance = f) Pearson = omial] it] = [95% Conf0892075 .0028902 .0016491 .0659098071038076354908171011434311074656145524731527871429162138399313724042157680705664	60256
Intrinsic est: Optimization Deviance Pearson Variance funct Link function Log likelihood	imator of APC : ML = 59273.9 = 60300.6 ion: V(u) = u : g(u) = 1 d = -29636.9 Coef0260843 .0603317 .0575739 .12404040099002010140101239110747186038314607039712628813090137409082061685570197463 .7235178	effects 95952 59232 1*(1-u/1) ln(u/(1-u)) 97976 OIM Std. Err. .0322063 .0293075 .0285336 .029659 .0311933 .0337837 .035058	-0.81 2.06 2.02 4.18 -0.32 -0.35 -2.13 -1.09 -1.84 -9.83 -3.47 -3.66 -3.83 -7.00 -0.76 18.51	No. Resi Scal (1/d (1/d [Bin [Log AIC BIC P> z 0.418 0.040 0.044 0.000 0.751 0.764 0.726 0.033 0.277 0.066 0.000 0.001 0.000 0.000 0.000 0.000 0.000 0.000 0.000 0.000 0.000	dual df = e parameter = f) Deviance = f) Pearson = omial] it] = = =	60256
Intrinsic est: Optimization Deviance Pearson Variance funct Link function Log likelihood	imator of APC : ML = 59273.9 = 60300.6 ion: V(u) = u : g(u) = 1 d = -29636.9 Coef	effects 95952 59232 1*(1-u/1) ln(u/(1-u)) 97976 OIM Std. Err. 0322063 0293075 0285336 029659 0311933 0337837 035058 035058 035058 0352818 0383311 0267339 0262969 0246239 023684 0240877 0259291	z -0.81 2.06 2.02 4.18 -0.32 -0.35 -2.13 -1.09 -1.84 -9.83 -3.47 -3.66 -3.83 -7.00 -0.76	No. Resi Scal (1/d (1/d [Bin [Log AIC BIC P> z 0.418 0.040 0.044 0.000 0.751 0.764 0.726 0.033 0.277 0.066 0.000 0.001 0.000 0.001 0.000 0.000 0.000 0.446	dual df = e parameter = f) Deviance = f) Pearson = omial] it] = [95% Conf0892075 .0028902 .0016491 .0659098071038076354908171011434311074656145524731527871429162138399313724042157680705664	60256
Intrinsic est: Optimization Deviance Pearson Variance funct Link function Log likelihood poldisc age_20 age_25 age_30 age_35 age_40 age_45 age_50 age_55 age_60 age_65 period_1975 period_1980 period_1985 period_1990 period_2005 cohort_1910	imator of APC : ML = 59273.9 = 60300.6 ion: V(u) = u : g(u) = 1 d = -29636.9 Coef0260843 .0603317 .0575739 .12404040090020101401012391107471860383146070397126288130913752090137409082061685570197463 .72351781822511	effects 95952 59232 1*(1-u/1) ln(u/(1-u)) 97976 OIM Std. Err 0322063 .0293075 .0285336 .029659 .0311933 .0337837 .03558 .035058	-0.81 2.06 2.02 4.18 -0.32 -0.35 -2.13 -1.09 -1.84 -9.83 -3.47 -3.66 -3.83 -7.00 -0.76 18.51 -2.06	No. Resi Scal (1/d (1/d [Bin [Log AIC BIC P> z 0.418 0.040 0.044 0.000 0.751 0.764 0.726 0.033 0.277 0.066 0.000 0.001 0.000 0.000 0.000 0.000 0.000 0.000 0.000 0.000 0.000 0.000 0.000 0.000 0.000 0.000 0.000	dual df = e parameter = f) Deviance = f) Pearson = omial] it] = =	60256
Intrinsic est: Optimization Deviance Pearson Variance funct Link function Log likelihood	imator of APC : ML = 59273.9 = 60300.6 ion: V(u) = u : g(u) = 1 d = -29636.9 Coef. 0260843 .0603317 .0575739 .124040400990020101401012391107471860383146070397126288130913752090137409082061685570197463 .723517818225111313027	effects 95952 69232 1*(1-u/1) ln(u/(1-u)) 97976 OIM Std. Err. .0322063 .0293075 .0285336 .029659 .0311933 .0337837 .0353675 .035058 .0352818 .0353811 .0267339 .0246239 .0246239 .0246239 .0246239 .023684 .0240877 .0259291 .0390873 .0886362 .0665408	-0.81 2.06 2.02 4.18 -0.32 -0.30 -0.35 -2.13 -1.09 -1.84 -9.83 -3.47 -3.66 -3.83 -7.00 -0.76 18.51 -2.06 -1.97	No. Resi Scal (1/d) (1/d) [Bin [Log AIC BIC 0.418 0.040 0.044 0.000 0.751 0.764 0.726 0.033 0.277 0.066 0.000 0.001 0.000 0.000 0.000 0.000 0.000 0.000 0.000 0.040 0.040 0.048	dual df = e parameter = f) Deviance = f) Pearson = omial] it] =	60256

```
    cohort_1930 | .0377907
    .0445031
    0.85
    0.396
    -.0494336
    .1250151

    cohort_1935 | .1101551
    .0425261
    2.59
    0.010
    .0268054
    .1935048

    cohort_1940 | .2436063
    .0401667
    6.06
    0.000
    .1648809
    .3223316

    cohort_1945 | .3278682
    .0381874
    8.59
    0.000
    .2530222
    .4027141

    cohort_1945 | .3103211
    .3278682
    .960581
    9.61
    0.000
    .2306486
    .3000037

                            .3103211 .0360581
.3025163 .035182
                                                                                                      .2396486
                                                                       8.61 0.000
8.60 0.000
 cohort_1950
                                                                                                                             .3809937
                                                  .035182
                                                                                                       .2335608
 cohort_1955
                                                                                                                             .3714718
                                                                                                                            .1565699

      cohort_1960
      .0880664
      .0349514
      2.52
      0.012
      .0195629
      .1565699

      cohort_1965
      -.0044316
      .0361802
      -0.12
      0.903
      -.0753435
      .0664803

      cohort_1970
      -.0337764
      .0406714
      -0.83
      0.406
      -.1134908
      .0459381

      cohort_1975 | -.0076029
      .0521615
      -0.15
      0.884
      -.1098375
      .0946317

      cohort_1980 | -.1241286
      .0711743
      -1.74
      0.081
      -.2636277
      .0153705

      cohort_1985 | -.8286148
      .1797071
      -4.61
      0.000
      -1.180834
      -.4763953

      _cons | 1.305779
      .0179028
      72.94
      0.000
      1.270691
      1.340868

                                                                                          No. of obs = 58644
Residual df = 58614
Scale parameter = 1
(1/df) Deviance = .8628025
Intrinsic estimator of APC effects
Optimization : ML
Deviance
                             = 50572.30835
                                                                                          (1/df) Pearson = 1.000243
                          = 58628.27182
Variance function: V(u) = u*(1-u/1)
                                                                                          [Binomial]
Link function : g(u) = \ln(u/(1-u))
                                                                                          [Logit]
                                                                                           AIC
                                                                                                                       = .8633843
                                                                                           BIC
Log likelihood = -25286.15418
                                                                                                                     = -592964.9
                                                      OIM
                                 Coef. Std. Err.
                                                                           z P> | z |
                                                                                                      [95% Conf. Interval]
        poldisc
______

    age_20
    .0297628
    .0367832
    0.81
    0.418
    -.0423309
    .1018565

    age_25
    .1197342
    .0338916
    3.53
    0.000
    .0533079
    .1861605

    age_30
    .0120017
    .0342646
    0.35
    0.726
    -.0551557
    .0791591

    age_35
    .0353367
    .0346144
    1.02
    0.307
    -.0325063
    .1031797

                             .024168 .0353683
.0713891 .0369658

      0.68
      0.494
      -.0451525
      .0934885

      1.93
      0.053
      -.0010624
      .1438407

      0.66
      0.511
      -.0479754
      .0964675

          age_40 |
                             .0713891 .0369658
.0242461 .0368483
          age 45
          age_50
                                               .0372643
                           -.0359878
                                                                      -0.97 0.334 -.1090245
-1.47 0.140 -.1214819
                                                                                                                             .037049
          age_55
                                                                                                                          .0171647
          age_60
                            -.0521586
          age_65 | -.2284923 .0357945 -6.38 0.000 -.2986483 -.1583362
 period_1975 | -.3735044 .0287902 -12.97 0.000 -.4299322 -.3170767 period_1980 | -.0832068 .0286957 -2.90 0.004 -.1394493 -.0269644
                           .003236 .0270828 0.12 0.905 -.0498452 .0563173
.185807 .0274657 6.77 0.000 .1319751 .2396388
 period_1985 |
period_1990 |
                                                                                                     .1319751 .2396388
-.146935 -.0414385
                                                                       -3.50 0.000
 period_1995 | -.0941867 .0269129
 period_2000 | .0631721 .028927
period_2005 | .298683 .0383835
                                                                      2.18 0.029
7.78 0.000
                                                                                                     .0064762
                                                                                                                             .119868
                                                                                                                             .3739133
                                                                                                       .2234527
                                                                      cohort_1910 | -.2444011 .0825749
                                                  .0628121
  cohort_1915 |
                           -.2042919
                                                                       0.64 0.522 -.0721211
                             .0349599 .0546342
                                                                                                                            .1420409
 cohort_1920
 cohort_1925 | -.1596874 .0446964
cohort_1930 | -.0433845 .0438978
                                                                      -3.57 0.000 -.2472908
-0.99 0.323 -.1294226
                                                                                                                              -.072084
                                                                                                                             .0426536
                           .1646393 .0415843 3.96 0.000 .0831355
.1937827 .0389466 4.98 0.000 .1174487
.2496426 .0419388 5.95 0.000 .1674441
                                                                                                                              .246143
 cohort_1935
                                                                                                                             .2701167
 cohort_1940
                             .2496426 .0419388
                                                                                                                             .3318411
 cohort_1945
                                                                                                    .1936195 .3572306
.1396812 .2978062
.1514213 .3084571
 cohort_1950 |
cohort_1955 |
                            .275425 .0417383
.2187437 .0403388
                                                                      6.60 0.000
5.42 0.000
                                                                                                                             .3572306
                            .2299392 .0400609 5.74 0.000
 cohort_1960
                                                                                                                         .1647342

      Cohort_1965
      .0851261
      .0406171
      2.10
      0.036
      .005518
      .1647342

      cohort_1970
      -.0213333
      .0434842
      -0.49
      0.624
      -.1065609
      .0638942

      cohort_1975
      -.2014412
      .0562576
      -3.58
      0.000
      -.3117042
      -.0911783

      cohort_1980
      -.1511164
      .0752256
      -2.01
      0.045
      -.298556
      -.0036769

      cohort_1985
      -.4266026
      .1374931
      -3.10
      0.002
      -.6960841
      -.1571211

 cohort_1965 | .0851261 .0406171
cohort_1970 | -.0213333 .0434842
         _cons | 1.571463 .0164465
                                                                     95.55 0.000
                                                                                                     1.539228 1.603697
 ______
***********
                                                                                          No. of obs = 60697

Residual df = 60667

Scale parameter = 1

(1/df) Deviance = 1.19269

(1/df) Pearson = .9997493
Intrinsic estimator of APC effects
Optimization : ML
Deviance = 72356.8984
Pearson = 60651.78847
Variance function: V(u) = u*(1-u/1)
                                                                                          [Binomial]
Link function : g(u) = \ln(u/(1-u))
                                                                                        [Logit]
```

poldisc	 Coef.	OIM Std. Err.	z	P> z	[95% Conf.	Intervall
	+					
age_20	.0649053	.0277569	2.34	0.019	.0105027	.1193079
age_25	.1438714	.0268097	5.37	0.000	.0913254	.1964175
age_30	.0415682	.0279946	1.48	0.138	0133003	.0964367
age_35	.0788058	.0277279	2.84	0.004	.0244601	.1331515
age_40	0037308	.0276243	-0.14	0.893	0578734	.0504118
age_45	.0423933	.0287774	1.47	0.141	0140094	.0987959
age_50	.0355917	.0290382	1.23	0.220	0213221	.0925056
age_55	.0109554	.0281778	0.39	0.697	044272	.0661828
age_60	1424841	.0295112	-4.83	0.000	200325	0846432
age_65	2718763	.0297884	-9.13	0.000	3302605	2134921
period_1975	2250778	.0227939	-9.87	0.000	269753	1804026
period_1980	4344998	.0212253	-20.47	0.000	4761005	392899
period_1985	485618	.0202155	-24.02	0.000	5252396	4459964
period_1990	.0775733	.0211259	3.67	0.000	.0361672	.1189793
period_1995	.5558319	.0248047	22.41	0.000	.5072155	.6044483
period_2000	.4167834	.0246747	16.89	0.000	.3684218	.465145
period_2005	.0950069	.0280442	3.39	0.001	.0400414	.1499725
cohort_1910	2387165	.0800465	-2.98	0.003	3956046	0818283
cohort_1915	1302494	.0568222	-2.29	0.022	2416188	0188801
cohort_1920	0257649	.0435466	-0.59	0.554	1111147	.0595848
cohort_1925	0627109	.0367426	-1.71	0.088	1347251	.0093032
cohort_1930	2030811	.0344129	-5.90	0.000	2705292	135633
cohort_1935	1118274	.033082	-3.38	0.001	1766668	046988
cohort_1940	0065746	.0322282	-0.20	0.838	0697408	.0565915
cohort_1945	.1747005	.0331737	5.27	0.000	.1096812	.2397199
cohort_1950	.3307405	.0332414	9.95	0.000	.2655886	.3958924
cohort_1955	.3343422	.0315581	10.59	0.000	.2724895	.3961949
cohort_1960	.1964612	.0310204	6.33	0.000	.1356623	.25726
cohort_1965	.0776325	.0321082	2.42	0.016	.0147015	.1405635
cohort_1970	.0682785	.0355266	1.92	0.055	0013522	.1379093
cohort_1975	0240678	.0423993	-0.57	0.570	1071688	.0590332
cohort_1980	1148518	.0554907	-2.07	0.038	2236117	006092
cohort_1985	264311	.109499	-2.41	0.016	4789251	0496969
_cons	.7732532	.0135772	56.95	0.000	.7466425	.799864
******	*****	******	*****	*****		

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Intrinsic estim	nator of APC effects	No. of obs =	25407
Optimization	: ML	Residual df =	25377
		Scale parameter =	: 1
Deviance	= 28433.41458	(1/df) Deviance =	1.12044
Pearson	= 25411.70239	(1/df) Pearson =	1.001367

AIC = 1.121479 BIC = -228959.9 Log likelihood = -14216.70729

		OIM				
poldisc	Coef.	Std. Err.	z	P> z	[95% Conf.	<pre>Interval]</pre>
age_20	0805502	.0481183	-1.67	0.094	1748603	.0137598
age_25	.013634	.045148	0.30	0.763	0748544	.1021224
age_30	075069	.0439951	-1.71	0.088	1612977	.0111598
age_35	0034846	.0424007	-0.08	0.935	0865885	.0796193
age_40	028118	.0441489	-0.64	0.524	1146483	.0584123
age_45	.037184	.0466501	0.80	0.425	0542486	.1286165
age_50	.0664384	.0491042	1.35	0.176	029804	.1626808
age_55	.026399	.0491605	0.54	0.591	0699537	.1227518
age_60	0294835	.0500188	-0.59	0.556	1275186	.0685516
age_65	.0730499	.0527004	1.39	0.166	030241	.1763408
period_1975	.0529725	.0461115	1.15	0.251	0374044	.1433494
period_1980	.0096309	.042258	0.23	0.820	0731933	.0924552
period_1985	1646977	.0390205	-4.22	0.000	2411764	0882189
period_1990	.1155184	.0350977	3.29	0.001	.0467282	.1843087
period_1995	1003686	.0308807	-3.25	0.001	1608936	0398435
period_2000	.0053724	.0330318	0.16	0.871	0593688	.0701136
period_2005	.0815719	.0446816	1.83	0.068	0060025	.1691464
cohort_1910	.1820813	.1750039	1.04	0.298	1609201	.5250827
cohort_1915	4269701	.1062052	-4.02	0.000	6351285	2188116

cohort_1920 cohort_1925 cohort_1930 cohort_1935 cohort_1940 cohort_1945 cohort_1950 cohort_1950 cohort_1960 cohort_1965 cohort_1970	1999594 0894281 1378759 .1812265 .1895636 .3633312 .3423266 .3533812 .2644717 .0040066 1431364	.0872192 .0736476 .0625952 .0612743 .0567867 .0571057 .053944 .0496741 .0485689 .046881 .0492025	-2.29 -1.21 -2.20 2.96 3.34 6.36 6.35 7.11 5.45 0.09 -2.91	0.022 0.225 0.028 0.003 0.001 0.000 0.000 0.000 0.000 0.932 0.004	3709059 2337748 2605602 .0611311 .0782636 .2514062 .2365983 .2560219 .1692784 0878785	029013 .0549186 0151916 .3013219 .3008635 .4752563 .4480549 .4507406 .3596649 .0958917 0467013
cohort_1975 cohort_1980 cohort_1985 _cons	2467676 393287 2429643 .9911792	.0581514 .0796703 .1688526 .0234811	-4.24 -4.94 -1.44 42.21	0.000 0.000 0.150 0.000	3607423 5494378 5739093 .9451571	1327929 2371362 .0879808 1.037201
**************************************	******	******	*****	*****		
Intrinsic esti	mator of APC : ML	effects		Resi	dual df =	= 58129 = 58099
Deviance Pearson	= 56050 = 58144.6			(1/d	e parameter = f) Deviance = f) Pearson =	.9647408
Variance funct Link function		u*(1-u/1) ln(u/(1-u))		[Bin [Log	omial] it]	
Log likelihood	d = -28025.2	23835		AIC BIC		= .9652751 = -581320
poldisc	Coef.	OIM Std. Err.	z	P> z	[95% Conf.	. Interval]
age_20 age_25 age_30 age_35 age_40 age_45 age_55 age_60 age_55 age_60 age_65 period_1980 period_1985 period_1990 period_2000 period_2000 period_2000 cohort_1910 cohort_1915 cohort_1920 cohort_1935 cohort_1940 cohort_1945 cohort_1955 cohort_1960 cohort_1965 cohort_1970 cohort_1975 cohort_1980 cohort_1980 cohort_1985cons		.0324253 .0307452 .0310435 .0318223 .0339764 .0346913 .0345556 .0345556 .0353273 .0263165 .0251308 .0247626 .0257653 .0264275 .0279933 .0353137 .0817585 .05581972 .0478922 .0446705 .0430307 .0400969 .0381969 .0370117 .0367124 .0367242 .0367182 .0374931 .0432742 .0503192 .0677891 .1353965 .0157086	3.04 3.92 2.78 1.33 3.74 1.09 -1.37 -4.26 -3.49 -5.69 -13.75 -14.99 -5.11 7.23 4.96 8.31 8.93 -5.28 -3.21 -1.83 -0.84 0.50 0.02 4.87 8.56 6.82 7.30 3.99 1.48 1.36 -2.48 1.36 -2.48 84.26	0.002 0.000 0.005 0.183 0.000 0.278 0.170 0.001 0.011 0.013 0.000 0.000 0.000 0.000 0.000 0.000 0.000 0.001 0.011 0.013 0.000 0.	.035056 .0602721 .02547250199957 .060442803033115285214828718274892701694413444642599931750597 .1357804 .0791562 .1778162 .2460066591962730101711815029124982206277920777448 .1111773 .2442456 .1784891 .1937091 .076383501799740261224215058324118756016719 1.292792	.1621609 .180791 .1471609 .1047454 .193628 .1056574 .0202847 0793732 0512519 1316888 3102857 3274884 0779922 .2367786 .1827502 .287548 .3844336 2714751 0728881 .0062309 .0501231 .1058982 .0794322 .2609064 .3893288 .3223991 .3359362 .2238442 .1289729 .1435094 0178106 .0245409 0709272 1.354369
Intrinsic esti Optimization Deviance	: ML = 73476.7	77903		Resi Scal (1/d	dual df = e parameter = f) Deviance =	= 1.304213
Pearson Variance funct	= 56371.9 zion: V(u) = 1				f) Pearson =	= 1.000603

Link function : $g(u) = \ln(u/(1-u))$ [Logit]

AIC = 1.304584 Log likelihood = -36738.38952 BIC = -542841.6

	1	OIM				
poldisc	Coef.	Std. Err.	Z	P> z	[95% Conf.	Interval]
	+					
age_20	172517	.0250815	-6.88	0.000	2216759	1233581
age_25	1532519	.0255727	-5.99	0.000	2033734	1031304
age_30	0010789	.0246556	-0.04	0.965	0494029	.0472451
age_35	0329901	.0262696	-1.26	0.209	0844775	.0184974
age_40	.1281739	.0287695	4.46	0.000	.0717866	.1845611
age_45	.1027357	.0284056	3.62	0.000	.0470618	.1584096
age_50	.0554154	.0299208	1.85	0.064	0032283	.1140591
age_55	.020388	.0299568	0.68	0.496	0383262	.0791022
age_60	.0366712	.0308171	1.19	0.234	0237293	.0970716
age_65	.0164536	.0311456	0.53	0.597	0445906	.0774978
period_1975	1101067	.0235908	-4.67	0.000	1563438	0638695
period_1980	.0583339	.0227277	2.57	0.010	.0137884	.1028793
period_1985	0117262	.0212633	-0.55	0.581	0534016	.0299491
period_1990	.0094429	.0203819	0.46	0.643	0305049	.0493908
period_1995	0886616	.0212679	-4.17	0.000	1303459	0469773
period_2000	.0649007	.0221888	2.92	0.003	.0214115	.1083899
period_2005	.0778169	.0269334	2.89	0.004	.0250285	.1306054
cohort_1910	2295234	.0808286	-2.84	0.005	3879445	0711024
cohort_1915	0755461	.0592748	-1.27	0.202	1917225	.0406303
cohort_1920	1292059	.0453202	-2.85	0.004	2180319	04038
cohort_1925	.0157687	.0395588	0.40	0.690	0617652	.0933025
cohort_1930	.1471496	.0373911	3.94	0.000	.0738643	.2204349
cohort_1935	.1663019	.0358552	4.64	0.000	.0960269	.2365768
cohort_1940	.2476279	.0349917	7.08	0.000	.1790454	.3162104
cohort_1945	.2978885	.0325514	9.15	0.000	.234089	.361688
cohort_1950	.2371181	.0306435	7.74	0.000	.1770579	.2971783
cohort_1955	.2280525	.0279268	8.17	0.000	.1733171	.282788
cohort_1960	.1475508	.0281285	5.25	0.000	.09242	.2026817
cohort_1965	.0422052	.0292742	1.44	0.149	0151712	.0995817
cohort_1970	0572063	.0314154	-1.82	0.069	1187793	.0043667
cohort_1975	1604655	.0369594	-4.34	0.000	2329046	0880263
cohort_1980	3978962	.0446434	-8.91	0.000	4853957	3103966
cohort_1985	4798199	.0901184	-5.32	0.000	6564486	3031911
_cons	.4488647	.0126473	35.49	0.000	.4240764	.473653

uk

Intrinsic estimator of APC effects
Optimization : ML Residual df = 58484
Scale parameter = 1
Deviance = 72382.78864 (1/df) Deviance = 1.237651
Pearson = 58515.52589 (1/df) Pearson = 1.000539

Variance function: V(u) = u*(1-u/1) [Binomial] Link function : g(u) = ln(u/(1-u)) [Logit]

AIC = 1.238042 Log likelihood = -36191.39432 BIC = -569597.3

		OIM				
poldisc	Coef.	Std. Err.	z	P> z	[95% Conf.	Interval]
age_20	1935516	.0260555	-7.43	0.000	2446194	1424838
age_25	0579975	.0261108	-2.22	0.026	1091737	0068212
age_30	.0321542	.0252508	1.27	0.203	0173365	.0816448
age_35	0183448	.0260974	-0.70	0.482	0694948	.0328052
age_40	.0376631	.0283835	1.33	0.185	0179676	.0932938
age_45	.0259213	.0293677	0.88	0.377	0316383	.0834809
age_50	.0025123	.0305088	0.08	0.934	0572839	.0623084
age_55	.1077777	.030906	3.49	0.000	.047203	.1683524
age_60	.052809	.0300444	1.76	0.079	0060769	.1116949
age_65	.0110563	.0303558	0.36	0.716	0484399	.0705525
period_1975	.0134943	.023763	0.57	0.570	0330803	.060069
period_1980	0002677	.0225805	-0.01	0.991	0445246	.0439893
period_1985	.0701091	.0218553	3.21	0.001	.0272735	.1129448
period_1990	.2352022	.0212458	11.07	0.000	.1935613	.2768432
period_1995	1614721	.0209775	-7.70	0.000	2025871	120357
period_2000	2037608	.0218494	-9.33	0.000	2465848	1609369
period_2005	.0466949	.0289946	1.61	0.107	0101336	.1035233

A3-b Synthetic results provided by APC-IE

	(1) poldisc	(2) poldisc	(3) poldisc	(4) poldisc	(5) poldisc	(6) poldisc	(7) poldisc	(8) poldisc	(9) poldisc
age_20	0.0837	0.0420	-0.0261	0.0298	0.0649	-0.0806	0.0986	-0.173	-0.194
age_25	0.0608	0.0581	0.0603	0.120	0.144	0.0136	0.121	-0.153	-0.0580
age_30	0.00133	0.0361	0.0576	0.0120	0.0416	-0.0751	0.0863	-0.00108	0.0322
age_35	0.0646	0.00628	0.124	0.0353	0.0788	-0.00348	0.0424	-0.0330	-0.0183
age_40	0.00357	0.0149	-0.00990	0.0242	-0.00373	-0.0281	0.127	0.128	0.0377
age_45	-0.0103	0.0774	-0.0101	0.0714	0.0424	0.0372	0.0377	0.103	0.0259
age_50	-0.0231	0.0456	-0.0124	0.0242	0.0356	0.0664	-0.0475	0.0554	0.00251
age_55	-0.0558	-0.0622	-0.0747	-0.0360	0.0110	0.0264	-0.147	0.0204	0.108
age_60	-0.0236	-0.0929	-0.0383	-0.0522	-0.142	-0.0295	-0.117	0.0367	0.0528
age_65	-0.101	-0.125	-0.0704	-0.228	-0.272	0.0730	-0.201	0.0165	0.0111
period_1975	0.0215	-0.457	-0.263	-0.374	-0.225	0.0530	-0.362	-0.110	0.0135
period_1980	-0.217	-0.326	-0.0914	-0.0832	-0.434	0.00963	-0.377	0.0583	-0.000268
period_1985	-0.168	-0.122	-0.0901	0.00324	-0.486	-0.165	-0.127	-0.0117	0.0701
period_1990	-0.119	0.104	-0.0908	0.186	0.0776	0.116	0.186	0.00944	0.235
period_1995	0.168	0.285	-0.169	-0.0942	0.556	-0.100	0.131	-0.0887	-0.161
period_2000	-0.00704	0.104	-0.0197	0.0632	0.417	0.00537	0.233	0.0649	-0.204
period_2005	0.321	0.411	0.724	0.299	0.0950	0.0816	0.315	0.0778	0.0467
cohort_1910	-0.307	-0.324	-0.182	-0.244	-0.239	0.182	-0.432	-0.230	-0.140
cohort_1915	-0.257	-0.351	-0.131	-0.204	-0.130	-0.427	-0.187	-0.0755	-0.124
cohort_1920	-0.0473	-0.0600	-0.0336	0.0350	-0.0258	-0.200	-0.0876	-0.129	-0.0171
cohort_1925	0.0207	-0.0467	-0.0746	-0.160	-0.0627	-0.0894	-0.0374	0.0158	0.00814
cohort_1930	-0.0700	-0.0213	0.0378	-0.0434	-0.203	-0.138	0.0216	0.147	0.130
cohort_1935	0.0791	0.0769	0.110	0.165	-0.112	0.181	0.000844	0.166	0.114
cohort_1940	0.218	0.225	0.244	0.194	-0.00657	0.190	0.186	0.248	0.211
cohort_1945	0.320	0.283	0.328	0.250	0.175	0.363	0.317	0.298	0.309
cohort_1950	0.301	0.283	0.310	0.275	0.331	0.342	0.250	0.237	0.258
cohort_1955	0.232	0.232	0.303	0.219	0.334	0.353	0.265	0.228	0.123
cohort_1960	0.141	0.136	0.0881	0.230	0.196	0.264	0.150	0.148	0.0450
cohort_1965	-0.0326	0.0750	-0.00443	0.0851	0.0776	0.00401	0.0555	0.0422	-0.0965
cohort_1970	-0.0757	-0.0931	-0.0338	-0.0213	0.0683	-0.143	0.0587	-0.0572	-0.172
cohort_1975	-0.127	-0.0987	-0.00760	-0.201	-0.0241	-0.247	-0.116	-0.160	-0.198
cohort_1980	-0.270	-0.196	-0.124	-0.151	-0.115	-0.393	-0.108	-0.398	-0.167
cohort_1985	-0.124	-0.119	-0.829	-0.427	-0.264	-0.243	-0.336	-0.480	-0.283
_cons	0.719	0.340	1.306	1.571	0.773	0.991	1.324	0.449	0.694

A3-c Detailed results provided by HAPC

We thank Fred Pampel for the STATA syntax developed in his paper (Pampel and Hunter 2012) that we could adapt our case

fr Mixed-effects Group variable		ession		Number o	f obs = f groups = group: min = avg =	58907.0
Integration po				Wald chi		8.11
poldisc	Coef.	Std. Err.	z	P> z	[95% Conf.	Interval]
zaq	.1020267	.0480574	2.12	0.034	.0078359	.1962175
zag2		.0108907	-1.72	0.086	0400574	.0026332
_cons	.7548571	.0844765	8.94	0.000	.5892862	.920428
Random-effec	ts Parameters	Estima	te Std	l. Err.	[95% Conf.	Interval]
_all: Identity	,	İ				
	sd(R.ye5)	.13223	85 .03	379975	.0752963	.2322429
	·	·-+				
_all: Identity	sd(R.co5)	.25075	22 .07	25175	.1422582	.4419897
		<u>-</u>				
LR test vs. lo	gistic regress	sion: ch	i2(2) =	384.39	Prob > chi	.2 = 0.0000
********	******	*****	****			
be						
	logistic regre	ession			f obs =	
Group variable	e: _all				f groups =	
				Obs per	group: min = avg =	
					max =	
Integration po	ints = 1			Wald chi		
Log likelihood				Prob > cl	hi2 =	0.0016
	Coof	Ctd Exa		P> z		
poldisc +	Coef.	Std. Err.	Z 		. [95% COIII.	Interval]
zag	.0652236	.0530665	1.23	0.219	0387848	.1692321
zag2		.0104224	-3.24		0542344	
_cons	.3748489	.1087506	3.45	0.001	.1617015	.5879962
Random-effec	ts Parameters	Estima	te Std	l. Err.	[95% Conf.	Interval]
_all: Identity	•					
	sd(R.ye5)	.22999	08 .07	03341	.1262997	.4188115
_all: Identity	,	-+ 				
_aii. identity	sd(R.co5)	.24006	92 .07	15703	.1338361	.4306255
ID togt vg lo	gistic regress	ion: ah	 :2(2) -	1051 21	Drob > chi	2 - 0 0000
LR CESC VS. IC	gistic regress	51011. CII	12(2) =	1051.31	Prob > CIII	.2 = 0.0000
	**********	******	*****			
nl	7			27	e -1	50560
Mixed-effects Group variable	-	ession			f obs = f groups =	
Group variable	· _a11				group: min =	
					avg =	
					max =	
Integration po				Wald chi		13.60
Log likelihood	1 = -29258.435			Prob > cl	n12 =	0.0011
poldisc	Coef.	Std. Err.	z 	P> z	[95% Conf.	Interval]
zag	.0680897	.0551567	1.23	0.217	0400155	.1761948
zag2						
_cons	1.377948	.1115518	12.35	0.000	1.159311	1.596586
Random-effec	ts Parameters	Estima	te Std	l. Err.	[95% Conf.	Interval]

_all: Identity		1				
	sd(R.ye5)	.255744	.073	32369	.1458977	.4482934
_all: Identity		+				
	sd(R.co5)	.2000396	.068	33504	.1023938	.3908033
LR test vs. lo	gistic regressi	on: chi2(2) =	505.95	Prob > chi	i2 = 0.0000
*****	******	*****	***			
de Mixed-effects	logistic regres	sion		Number of	obs =	= 57639
Group variable				Number of	groups =	= 1
				obs per gr	coup: min = avg =	
Integration po	inta = 1			Wald chi2	max =	
Log likelihood				Prob > chi		= 0.0000
poldisc	Coef. S	td. Err.	z	P> z	[95% Conf.	. Interval]
zag	 0268978 .	0315518 -0	 85	0.394 -	 0887381	.0349425
zag2	0626181 .	0139607 -4	1.49	0.000 -	0899805	0352557
_cons	1.637388 . 	0854762 19).16 	0.000 	1.469857 	1.804918
Pandom-effect	 ts Parameters	 Estimate	 5+2	 Frr	 [95% Conf	. Interval]
		+		. EII.		
_all: Identity	sd(R.ye5)	.1924117	.055	53456	.109494	.3381213
_all: Identity		+				
_all: identity	sd(R.co5)	.1590284	.036	54438	.1014867	.2491958
LR test vs. lo	gistic regressi	on: chi2(2) =	325.22	Prob > chi	L2 = 0.0000
******	*****	******	***			
it				1		50505
Group variable	logistic regres : _all	sion			obs = groups =	
				Obs per gr	coun: min =	- E0707
				opp ber ar	_	
					avg = max =	= 59797.0 = 59797
Integration po				Wald chi2(Prob > chi	avg = max = (2) =	59797.0
Log likelihood	= -35622.133 	td Enn		Wald chi2(avg = max = (2) = i2 =	= 59797.0 = 59797 = 36.60 = 0.0000
	= -35622.133 		z	Wald chi2(avg = max = (2) = i2 =	59797.0 59797 36.60
Log likelihood poldisc zag	= -35622.133 	 0354764 -1	.62	Wald chi2(Prob > chi	avg = max = (2) = 12 =	= 59797.0 = 59797 = 36.60 = 0.0000 . Interval] .0119134
Log likelihood poldisc zag zag2	= -35622.133 Coef. S 	0354764 -1 0108143 -5 1453749 5	.62 5.84 5.68	Wald chi2() Prob > chi	avg = max = (2) =	= 59797.0 = 59797 = 36.60 = 0.0000 . Interval] .0119134 0419908 1.111352
Log likelihood poldisc zag zag2 cons	= -35622.133 Coef. S 0576191 . 0631865 . .8264229 .	0354764 -1 0108143 -5 1453749 5	62 6.84 6.68	Wald chi2() Prob > chi P> z 0.104 - 0.000 - 0.000	avg = max = (2) = 12 = [95% Conf12715150843822 .5414935	= 59797.0 = 59797 = 36.60 = 0.0000 . Interval] .0119134 0419908 1.111352
Log likelihood poldisc zag zag2 cons Random-effec	= -35622.133 Coef. S 	0354764 -1 0108143 -5 1453749 5	62 5.84 5.68	Wald chi2() Prob > chi P> z 0.104 - 0.000 - 0.000	avg = max = (2) =	= 59797.0 = 59797 = 36.60 = 0.0000 . Interval] .0119134 0419908 1.111352
Log likelihood poldisc zag zag2 _cons Random-effec	Coef. S057619106318658264229	0354764 -1 0108143 -5 1453749 5 	62 6.84 6.68 Std.	Wald chi2() Prob > chi	avg = max = (2) =	= 59797.0 = 59797 = 36.60 = 0.0000
Log likelihood poldisc zag zag2 _cons Random-effec	Coef. S057619106318658264229 .	0354764 -1 0108143 -5 1453749 5 	62 6.84 6.68 Std.	Wald chi2() Prob > chi	avg = max = (2) =	= 59797.0 = 59797 = 36.60 = 0.0000
Log likelihood poldisc zag zag2 _cons Random-effec	= -35622.133 Coef. S 0576191 . 0631865 . .8264229 . ts Parameters sd(R.ye5)	0354764 -1 0108143 -5 1453749 5 	62 6.84 6.68 Std.	Wald chi2(Prob > chi P> z 0.104 - 0.000 - 0.000 . Err.	avg = max = (2) =	= 59797.0 = 59797 = 36.60 = 0.0000
poldisc	= -35622.133 Coef. S 057619106318658264229	0354764 -1 0108143 -5 1453749 5 	62 5.84 5.68 Std.	Wald chi2(Prob > chi P> z 0.104 - 0.000 - 0.000 . Err.	avg = max = (2) =	= 59797.0 = 59797 = 36.60 = 0.0000
poldisc zag zag2 cons Random-effect all: Identity LR test vs. log	= -35622.133 Coef. S057619106318658264229 . ts Parameters sd(R.ye5) sd(R.co5)	0354764 -1 0108143 -5 1453749 5 	62 6.84 6.68 Std	Wald chi2(Prob > chi P> z 0.104 - 0.000 - 0.000 . Err.	avg = max = (2) =	= 59797.0 = 59797 = 36.60 = 0.0000
poldisc zag zag2 cons Random-effect all: Identity LR test vs. log	= -35622.133 Coef. S 057619106318658264229	0354764 -1 0108143 -5 1453749 5 	62 6.84 6.68 Std	Wald chi2(Prob > chi P> z 0.104 - 0.000 - 0.000 . Err.	avg = max = (2) =	= 59797.0 = 59797 = 36.60 = 0.0000
poldisc zag zag2 cons Random-effect all: Identity LR test vs. log ***********************************	= -35622.133 Coef. S 057619106318658264229 . ts Parameters sd(R.ye5) sd(R.co5) gistic regressi	0354764 -1 0108143 -5 1453749 5 	62 6.84 6.68 Std	Wald chi2(Prob > chi	avg = max = (2) =	= 59797.0 = 59797 = 36.60 = 0.0000
Log likelihood poldisc zag zag2 _cons Random-effec _all: Identity LR test vs. log	= -35622.133 Coef. S 057619106318658264229 . ts Parameters sd(R.ye5) sd(R.co5) gistic regressi	0354764 -1 0108143 -5 1453749 5 		Wald chi2() Prob > chi	avg = max = (2) =	= 59797.0 = 59797 = 36.60 = 0.0000
poldisc zag zag2 cons Random-effect all: Identity LR test vs. log ***********************************	= -35622.133 Coef. S 057619106318658264229 . ts Parameters sd(R.ye5) sd(R.co5) gistic regressi	0354764 -1 0108143 -5 1453749 5 		Wald chi2() Prob > chi	avg = max = (2) =	= 59797.0 = 59797 = 36.60 = 0.0000
poldisc	= -35622.133 Coef. S 057619106318658264229	0354764 -1 0108143 -5 1453749 5		Wald chi2() Prob > chi	avg = max = (2) =	= 59797.0 = 59797 = 36.60 = 0.0000
poldisc	= -35622.133 Coef. S 057619106318658264229 . ts Parameters sd(R.ye5) sd(R.co5) gistic regressi **********************************	0354764 -1 0108143 -5 1453749 5		Wald chi2(Prob > chi	avg = max = (2) =	= 59797.0 = 59797 = 36.60 = 0.0000
poldisc	= -35622.133 Coef. S 057619106318658264229	0354764 -1 0108143 -5 1453749 5		Wald chi2(Prob > chi P> z 0.104 - 0.000 - 0.000 . Err. 201105 26863 2004.30 Number of Number of Obs per gr	avg = max = (2) = (2) = (2) = (27) =	= 59797.0 = 59797 = 36.60 = 0.0000
poldisc	= -35622.133 Coef. S 057619106318658264229 . ts Parameters sd(R.ye5) sd(R.co5) gistic regressi **********************************			Wald chi2(Prob > chi	avg = max = (2) =	= 59797.0 = 59797 = 36.60 = 0.0000
poldisc	= -35622.133 Coef. S 057619106318658264229			Wald chi2(Prob > chi	avg = max = (2) =	= 59797.0 = 59797 = 36.60 = 0.0000

Random-effects	Parameters	Estimate	Std	. Err.	[95%	Conf.	Interval]
_all: Identity	sd(R.ye5)	.0859752	.02	89708	.044	4168	.1664177
_all: Identity	sd(R.co5)	.2331601	.04	93516	.1539	9875	.3530392
LR test vs. logi	stic regression	on: chi2	(2) =	149.53	Prob	> chi:	2 = 0.0000
******	*****	*****	****				
dk Mixed-effects lo Group variable:	_all	sion		Number of Number of Obs per gr	group:	min = avg = max =	1 57222 57222.0 57222
Integration poin Log likelihood =				Prob > ch:	(2) i2 		12.55 0.0019
poldisc		d. Err.		P> z	[95%	Conf.	Interval]
zag2	0434017 .0	.036253 -1 0130723 -3 1027811 13	3.32	0.001	069	4291 9023 6921	.01868 0177805 1.599815
Random-effects	Parameters	Estimate	Std	. Err.	[95%	Conf.	Interval]
_all: Identity	sd(R.ye5)	. 2449452	.07	00763	.1398	8135	.4291299
_all: Identity	ad (R. co5)	.158604	n4	21268	n94′	2381	2669329
LR test vs. logi							
********* ie Mixed-effects lo Group variable: Integration poin Log likelihood =	gistic regress _all ts = 1		***	Number of Number of Obs per gr Wald chi2 Prob > ch:	group:	ps = min = avg =	1 55371 55371.0
poldisc	Coef. St	d. Err.	z	P> z	[95%	Conf.	Interval]
zag zag2 _cons	.1464881 .(0792726 .(.4880586 .(0246458 ! 0106489 - 0534476 !	5.94 7.44 9.13	0.000	100	0144	.194793 0584012 .5928141
Random-effects			Std	 . Err.	 [95%	Conf.	Interval]
_all: Identity	sd(R.ye5)	.0604507	.02	00286	.031	5777	.1157237
_all: Identity	sd(R.co5)	.1764053					
LR test vs. logi							
**************** uk Mixed-effects lo	**************	* * * * * * * * * * * * *		Number of	obs	=	57498
Group variable:						avg = max =	57498 57498.0 57498
Integration poin Log likelihood =				Prob > ch	i.2	= = 	
poldisc	Coef. St						
zag zag2 _cons	.1100132 .0 0550215 .0 .7222993 .0	0246818 4 0107524 -9 0687724 10	1.46 5.12 0.50	0.000 0.000 0.000			.1583886 0339472 .8570907

Random-effects	'	Estimate		[95% Conf.	
_all: Identity	sd(R.ye5)	.1505477	.0420612	.0870681	.2603091
_all: Identity	sd(R.co5)	.1386182	.0293161	.0915802	.2098163
LR test vs. logis	tic regression:	chi2(2) = 465.45	Prob > chi2	2 = 0.0000
*******	******	*****	**		

A3-c Synthetic results provided by HAPC

co5	cohbefr	cohbebe	cohbenl	cohbede	cohbeit	cohbelu	cohbedk	cohbeie	cohbeuk
1916 1921 1926 1931	3335615 2342802 2905835	5561736 3457143 1996919 1822897	2856336 2562954 1654716	0925064 2096421 0524953	0735711 1571657 2392847	1466027 1488625 1304453	1679851 1385737 0724729	259824 1161091 .0095889	083012 0714455 .0266801
1936 1941	0766184 .1110336		0336737 .0870777		1324391 0472685	.1827483	0798193 .1249022	.0391426 .1785045	.0606641 .1365631
1946 1951	.2094941	.2412185	.2334116	.1496783	.1285602	.2882922	.2190644	.2288069 .1793634	.2431339
1956 1961	.2474161 .2055959	.2485648	.2223348	.1396665 .1867206	.2853175	.3040007	.1696344	.2049869	.1005695 .0121101
1966	.0932328	.1580256	.0226924	.0274616	.0413082	0765561	.0559671	.0508352	1059229
1971 1976 1981	.1145528 .0796793 .1349462	.0470242 .0601424 .024673	.0559735	1000102 1083068 1246336		1285644 2710211 209196		0786897	1153156
	cohbsefr	cohbsebe	cohbsenl	cohbsede	cohbseit	cohbselu	cohbsedk	cohbseie	cohbseuk
stderr	.04752	.0573279	.0552483	.0502657	.051267	.0517762	.0496685	.032534	.0404745

Appendix 4 – Results of the OLS regression of the detrended cohort coefficients of political participation (poldidge) on the country-specific detrended size of birth cohorts (demodge) and the country-specific detrended real economic growth, in log-gdp (lgdpdge)

A first correlation matrix shows that no variable is cohort-trended, and correlations are relatively strong (but not too strongly see below)

```
. pwcorr poldidce demodce lgdpdce c , star(.05)
```

	poldidce	demodce	lgdpdce	coh
poldidce	1.0000			
demodce	0.4763*	1.0000		
lgdpdce	0.4206*	0.4014*	1.0000	
coh	-0.0000	0.0000	-0.0000	1.0000

The OLS regression shows the role of both cohort size and economic growth in cohort bumps

```
. reg poldidce demodce lgdpdce, robust
```

poldidce	Coef.	Robust Std. Err.	t	P> t	[95% Conf.	Interval]
demodce	.5807928	.1273595	4.56	0.000	.3282626	.8333231
lgdpdce	.5047088	.18752	2.69	0.008	.1328913	.8765263
_cons	-5.79e-11	.0135691	-0.00	1.000	0269051	.0269051

The variance inflation factor shows that, even if the explanatory variables are correlated, we have no problem of excessive collinearity

. vif

Variable	VIF	1/VIF
demodce lgdpdce	1.19 1.19	0.838884 0.838884
Mean VIF	1.19	