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RESEARCH PAPER

Lonely in a Crowd: Cohort Size and Happiness in the United Kingdom

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Abstract

Studies have shown that happiness level varies significantly across birth cohorts and baby boomers are the unhappiest of all birth cohorts. Yet, we don't know if this is due to their large cohort size negatively affecting happiness. We question whether people born in high fertility times are unhappy because they suffer more from economic setbacks and/or social strains. Using 9 waves of data from the European Social Survey United Kingdom Subset 2002–2018 ($N=19{,}364$) and hierarchical age-period-cohort cross-classified models, we analyze the effects of cohort size, socioeconomic status, marital status, and sociality on happiness. Cohort size, marital status, and sociality are the top three factors of cohort difference in happiness, but socioeconomic status is not. Cohort size is negatively associated with happiness. Income, education, or employment are not the source of unhappiness among the Boomers. Besides being members of a large cohort, the Boomers have two known factors against their odds: they are the most likely to separate and divorce and the least likely to socialize with friends despite having a large number of peers. Social disintegration and deprivation, not economic impoverishment, appears to be the culprit of unhappiness of the UK Baby Boomers.

Keywords Happiness · Easterlin hypothesis · Cohort analysis · Baby boomers

1 Introduction

One well-known demographic puzzle is why baby boomers are the least happy among all birth cohorts (Bardo et al., 2017; Pew Research Center, 2008; Yang, 2008). Despite their life experiences of economic growth, the U.S. and U.K. baby boomers are the least happy among all birth cohorts. Evidence shows that American baby boomers encountered underemployment and are worse off economically (Easterlin, 1987; Slack & Jenson 2008). Despite speculations that members of larger cohorts tend to face more competition in the labor force, housing, the marriage market, intense sibling rivalry, higher income inequality, and fewer education opportunities (Bronson & Mazzocco, 2018; Easterlin, 1987, 2010; Macunovich & Easterlin, 2010), empirical examinations of these

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factors are scant. We do not know if these factors directly contribute to the unhappiness of the boomers. We also do not know if the boomers are unhappy because of their large cohort size, and if so, the pathways through which larger cohort size impacts happiness.

Research has assessed the socioeconomic consequences of cohort effects (Heer, 1985; Pampel & Peters, 1995; Macunovich, 1998, 2000; Slack & Jenson 2008), but studies that directly tested the link between cohort size and sense of happiness is limited (Yang & Land, 2013). Past research has focused on age variation in happiness without taking into account cohort and period aspects of the happiness process (Blanchflower & Oswald, 2004, 2008; 2017; Oswald & Powdthavee, 2008; Margolis & Myrskyla, 2011; Fukuda, 2013). Without differentiating age and cohort effects, we are unable to identify whether the boomers' unhappiness is due to reaching middle-age or a result of their birth times (Bardo, 2017; Yang & Land, 2013). Although the age effect was not trivial (Shek, 1996; Blanchflower & Oswald, 2008; 2017), a study shows the cohort variation in happiness was much larger compared to the age effect using samples of twentieth-century Americans (Sutin et al., 2013). Yang & Land (2013) conduct an extensive HAPC analysis of the relative cohort size effect on happiness. Our studies build upon their framework but use different specifications of cohort size variables and individual-level covariates.

Several studies have identified that the U.S. baby boomers are significantly gloomier than other generations (Yang, 2008; Slack & Jenson 2008; Fukuda, 2013; Sutin et al., 2013; Bardo et al., 2017). Without explicitly testing cohort size in the models, speculated that the large cohort size of the baby boomer generation might be the reason for their lower levels of happiness. Being a member of large cohort subjects the boomers to unique formative experiences in the family, school, and labor market that have a lasting impact on individuals' sense of happiness (Yang, 2008 p. 222). It is unclear if the cohort effect of baby boomers may be idiosyncratic to the historical and cultural conditions in the United States.

This research bridges these gaps by contributing to our knowledge on the impact of cohort size on subjective well-being in several ways. First, we test the impact of cohort size on happiness net of age, period, demographic characteristic, socioeconomic status (SES), marital status, and sociality. No previous studies have included cohort size explicitly in their analysis to verify if it is directly responsible for the happiness disparity.

Second, we investigate the mechanisms through which cohort size affects happiness. We further analyze whether cohort size influences happiness because members of large cohorts suffer from the lesser socioeconomic status as education, employment, and earning opportunities could be scarce. We also evaluate the social connections in family and marriage on happiness and whether being a member of large birth cohorts diminishes people's chances of entry into marriage, a known booster of happiness. We last consider whether members of a large cohort socialize differently and if this variation in social capital contributes to their lower sense of happiness.

Lastly, to rule out the unique experiences of the coming of age of the U.S. boomers, we test the link between cohort size and happiness in a different population with a distinct boomer generation. The U.K. Baby Boomers are the post-war generation born in 1946–1964. They are the largest birth cohort in the country and account for 20–30% of the UK's population at various historical times. The data from the U.K. will enable us to evaluate the link between cohort size and happiness, how the largest cohort impacts the life experiences of its members, and whether these mechanisms are not limited to the U.S.

2 Cohort Size and Well-Being

The relative cohort size hypothesis posits that the social and economic fortunes of a cohort tend to vary inversely with its relative size (Economic & Social Research Council, 2015; Macunovich & Easterlin, 2010). The relative cohort size is approximated by the crude birth rates around a period (Easterlin, 1987; Macunovich, 2000; Yang, 2008). The happiness formation process is intrinsically a cognitive and emotional process that is conditioned by individual and communal resources and physical conditions (Easterlin, 1987, 2001, 2004; Graham, 2008, 2009; Hagerty & Veenhoven, 2003). Physical conditions such as food, savings, wealth, and health are important. So are nonmaterial resources such as interpersonal connections. Being members of different birth cohorts of various sizes may give rise to distinct levels in both material and nonmaterial resources that compose the underlying processes of happiness formation (Macunovich & Easterlin, 2010).

2.1 Crowding in Large Cohorts

The "crowding mechanism" operates mainly through the institutions that shape one's earning potential because a large crowd of people will constrain the number of resources available in those institutions (Macunovich & Easterlin, 2010). The linkage between higher birth rates and adverse social and economic outcomes arises from crowding mechanisms that operate within three major social institutions—family, school, and labor market (Macunovich & Easterlin, 2010; Macunovich, 2000). Large cohorts strain institutions of social support and stretch family and community resources as they grow up with more children per family, more children per classroom, and more children per school and teacher. Because a relatively large birth cohort implies a higher sibling count and a shorter birth interval than a smaller one, children from this large birth cohort encounter more competition for material and social resources at home, at school, and in the job market against other peers outside of family and siblings within a family. A larger cohort size often implies individuals living with many siblings. A large number of siblings lowers parental happiness, increases sibling rivalry and delinquency at home, and lowers academic performance in school (Heer, 1985; Kohler et al., 2005).

Large cohort size reduces the efficiency of the matching in the marital market, creating a surplus of unmarried population (Bronson & Mazzocco, 2018). Therefore, more peers not only mean more competition but also imply a lower marriage rate. Since marriage is a known predictor of happiness (Stutzer & Frey, 2006), it is likely that a lower marriage rate among members of a large cohort will lead to less happiness.

A crowded cohort may also induce psychological distress as people from a large cohort are more likely to encounter stress and disappointment when unable to meet their social goals (Easterlin, 1987; Macunovich & Easterlin, 2010; Pampel & Peters, 1995). This size-based psychological stress can result in a higher chance of social malaise, crime, and suicide (Pampel & Peters, 1995; Stockard & O'Brien, 2002). The crowding effect between cohort size and happiness can be social and emotional because individuals compete for non-monetary resources, such as social status, social recognition, and political resources (Macunovich & Easterlin, 2010). Such distress may result from social and economic competition or a combination of actual competition and perception of aggregate economic scarcity, such as labor market competitiveness, employment rates, perceived income inequality, and sense of fairness (Slack & Jenson 2008; Oishi et al., 2011). Members of larger cohorts suffer from less social integration and support, thus are at greater risk for suicide throughout their life spans in the U.S. (Stockard & O'Brien, 2002). We thus hypothesize that members of smaller cohorts are happier than individuals from larger cohorts (Hypothesis A).

2.2 Material and Nonmaterial Sources of Happiness

Socioeconomic status (SES), i.e., income, education, employment status, and occupation status, has been identified as the strongest influence on self-reported happiness (Easterlin, 2004). Among these SES variables, average income is highly and positively associated with self-reported happiness, because wealthy people enjoy material satisfaction and being optimistic about future life outcomes (Hagerty & Veenhoven, 2003). Because people from larger cohorts are more likely to face more socioeconomic competition and hence less happy than those from smaller cohorts, we hypothesize that socioeconomic factors such as income, education, and employment status are responsible for the negative association between cohort size and happiness (Hypothesis B).

Interpersonal relationship, such as marital status, is an important source of happiness (Fukuda, 2013; Yang, 2008). Married individuals are happier than unmarried individuals either due to self-selection into marriage or additional social support from family members (Stuzer & Frey 2006; Kohler et al., 2005). Marital status also results in differential health and financial wellbeing that may lead to differences in happiness (Waite & Gallagher, 2001). Therefore, we hypothesize that marital status accounts for the negative association between cohort size and happiness (Hypothesis C).

Social connection or sociality is another determinant of self-reported happiness (Bruni, 2010; Delaney & Madigan, 2017). People who socialize more frequently with friends and family members are happier. Members of large birth cohorts may have more peers that provide opportunities for a larger friendship circle, but they do not automatically enjoy high sociality which emphases the frequency and quality of friendship rather than the quantity (Delaney & Madigan, 2017). Cohorts who socialize more often are happier than cohorts who socialize less often, and members of larger cohorts may socialize more than smaller cohorts because of the abundance of peers they have. We thus hypothesize that sociality may account for cohort size effect on happiness (Hypothesis D).

3 Data, Measures, and Modeling Strategy

We use data at two levels: individual and cohort. The individual-level data are from the European Social Survey United Kingdom subset (ESS hereafter). ESS is a repeated cross-sectional biennial pan-European social survey. The survey questions in the ESS closely resemble the questions in the United States General Social Survey. The full U.K. sample consists of 19,364 respondents in nine waves from 2002 to 2018.

The cohort-level data is from the Office of National Statistics (2017), a non-ministerial department under the UK Parliament, similar to the United States Census (ONS 2017). We derive all the yearly demographics data from the ONS report, such as the number of live births in the United Kingdom from 1900 to 2012. As for specifying the timeframe of each generation and birth cohort, we reference archival data from Halsey & Webb (2000) and Dimock (2019). The British cohort definitions in the twentieth century are virtually identical to that of the U.S. (ONS 2017; Halsey & Webb 2000; Fry, 2020).

Two measures, household income and marital status, have high nonresponses of about 20% of the data. The majority of missing in marital status is due to "refuse to answer," and the majority of missing in income status is due to "refuse to answer" and "don't know." These cases are not missing at random, so imputation methods are not appropriate (Lavrakas, 2008). Younger people and non-breadwinners are more likely to not know about their family income. The probabilities of missing data in income and marital status also vary significantly across gender, minority status, and age groups. We use two dummy variables to indicate the missing income and marital status (Allison 2001). Other variables in the full models have percentages of missing cases at less than 5%. After adjusting for item nonresponses with dummy variables, the analytic sample contains 19,364 cases.

3.1 Outcome Variable

We measure happiness from answers to the question, "Do you feel happy in general?" in an 11-point Likert scale, ranging from "extremely unhappy" to "extremely happy" (extremely unhappy, 1, 2, 3, 4, 5, 6, 7, 8, 9, and extremely happy). This measure has been proven to have high internal consistency and construct validity in measuring the psychometric properties of well-being or distress across different populations (Lyubomirsky & Lepper, 1999; Oswald & Wu, 2010; Reichhardt, 2006). We dichotomize this happiness scale by the middle point—classifying the 11 points ordinal scale into two categories of unhappy (including "extremely unhappy" to 5) and happy (6 to "extremely happy"). We make this decision out of several considerations. First, treating the measure as ordinal or continuous is problematic as the distribution is highly skewed with about 85% of respondents reporting happiness higher than 5, and less than 1% are in the lowest category of extremely unhappy.[1] Second, our priority is not to identify factors that maximize the degree of happiness but to identify factors that differentiate cohort-level happiness versus unhappiness. Third, following recommended solution for a disproportionate discrete dependent variable to categorize a Likert scale into fewer categories (MuthÉn & Speckart, 1983), we use five as the cutoff, because the middle point in a Likert scale should conceptually differentiate those who are happy and unhappy (MacCallum et al., 2002; Ragland, 1992).

The UK is among one of the happiest countries in the world which currently ranked 13th according to the World Happiness Report (Helliwell et al., 2020), which explains the high happiness reporting in the data. The General Social Survey data from the United States (2002–2018) currently ranked 18th have a similar percent of people report happy and fairly happy (85.7%) (Helliwell et al., 2020; Smith et al., 2018). Hence, 85% of British respondents who are happy, consistent with data from other similar countries such as the United States.

3.2 Independent Variables

Three variables indicate age, period, and birth cohorts. Age is set up as an individual level control variable in a hierarchical age-period-cohort model (Yang & Land, 2008). We also add an age squared term to account for the U-shaped quadratic age effect on happiness (Bardo et al., 2017; Blanchflower & Oswald, 2008; Clark, 2007; Sutin et al., 2013), and it adds a constraint to identify the APC parameters (Yang & Land, 2008, 2013). Period

[1] Dichotomization is a common solution for models with highly skewed continuous outcome variable.

(survey years) and cohort identification variables are cross-tabulated and set up as group-level control variables (Yang & Land, 2008). The survey consists of nine interview waves during 2002–2018. There are16 birth cohorts. We first identify a total of six generations of the Greatest generation (1900–1927),[2] the Silent Generation (1928–1945), Baby Boomers (1946–1964), Generation X (1965–1980), Millennials (1981–1996), and Generation Z (1997–2012).[3] We next divide each generation into three equal-sized cohorts according to other cohort studies that have similar data structures (Shu & Meagher, 2018; Shu & Ye Forthcoming).[4]

Average cohort size (ACS) is the average number of new births per 100,000 people per year for a birth cohort. For example, the average cohort size for the WWII cohort is the total number of new births in 1940–1945 divided by 6 years. We use ACS instead of the relative cohort size (RCS). RCS is the average *crude birth rate* in all the birth years of a birth cohort (Abeysinghe, 1991; Easterlin, 1987; Macunovich & Easterlin, 2010). A crude birth rate equals the number of new births in a given timeframe divided by the total mid-year population times one thousand. The RCS effect is difficult to interpret because the effect is confounded by the total population size. People in a birth cohort often compete with peers who are similar in age rather than the total population (Macunovich & Easterlin, 2010; Macunovich, 2000). The ACS effect statistically approximates a relative cohort size effect because the odds ratio of ACS in a Bernoulli model indicates the relative risk of being happy compared to a grand-mean centered reference cohort size.

Marital status is measured as a series of dummy variables indicating separated, divorced, widowed, never married or single, and unknown status with "married" as the reference group. The unknown marital status variable includes those who "refuse to answer" (4730 cases) and a few "don't know" or "no answer" (89 cases). Variables measuring socio-economic status include household income, education, and employment. Household income classifies an individual's annual household income in four categories: "lower-income class" with annual household income lower than 12,000 Euros, "middle-income class" with annual household income around 27,000 Euros, "upper-income class" with an annual household income of more than 60,000 Euros, and the household income unknown (1,306 "refuse to answer" and 2,135 "don't know). The lower-income class is omitted as the reference income level. Education is in five categories of "less than upper school" (0 ~ 10 years), "upper school completed" (11 ~ 12 years), "some college" (13 ~ 15 years), "college completed" (16 ~ 18 years), and "advance degree" (> 19 years). We recoded them into dummy variables with "less than upper school" as the reference category. Unemployment is a dichotomous variable with one indicative of a respondent unemployed in the last seven days and zero otherwise. The sociality variable measures how frequently respondents socialize with friends, relatives, and colleagues. We use a series of four dummy variables to represent "social monthly or several times a month," "social weekly," "social more than once a week," and "social every day," with "never social or social less than once a month" as the reference group.

[2] We put three respondents who were born prior to 1910 into one cohort because the number of people born in those years are too small.

[3] Generation Z has one birth cohort (1997–2003).

[4] Demographic research usually uses a uniform 5-year gap per cohort (Yang 2008). This uniform division of cohorts may not reflect the social and cultural differentiation of the experiences of people born in different years.

Table 1 Cross-classified data by cohorts and survey years (European Social Survey—UK 2002–2018)

Cohorts/Survey Years	2002	2004	2006	2008	2010	2012	2014	2016	2018	Total
Greatest I: pre-1910	1	0	1	1	0	0	0	0	0	3
Greatest II: 1910–1918	24	24	25	12	5	2	0	0	0	92
Greatest III: 1919–1927	190	115	155	105	88	67	32	19	0	771
Silent I: 1928–1933	147	133	143	133	112	134	102	66	71	1041
Silent II: 1934–1939	153	162	178	147	172	157	138	106	98	1311
Silent III: 1940–1945	180	161	225	191	202	200	212	128	158	1657
Baby Boomers I: 1946–52	256	163	271	280	294	284	282	264	270	2364
Baby Boomers II: 1953–58	177	167	214	193	226	209	201	185	213	1785
Baby Boomers III: 1959–64	231	212	233	257	252	219	243	180	262	2087
Generation X I: 1965–70	253	237	267	274	233	225	223	189	205	2103
Generation X II: 1971–75	171	165	192	201	195	167	188	150	154	1583
Generation X III: 1976–80	101	133	161	183	170	154	185	150	174	1411
Millennials I: 1981–86	133	131	167	175	200	162	175	189	218	1550
Millennials II: 1987–91	9	59	115	113	128	124	110	120	146	924
Millennials III: 1992–96	0	0	0	30	73	94	76	90	103	466
Generation Z: 1997–2012	0	0	0	0	0	14	44	70	88	216
Total	2034	1872	2370	2309	2372	2237	2219	1918	2171	19,364

We also include gender, minority status, foreign-born status, religiosity in the analyses as controls. Gender is a binary variable with one indicating female and zero otherwise. Minority indicates if a respondent belongs to a minority ethnic group (1: yes, 0: no). Foreign-born indicates if a respondent is born outside the United Kingdom (1: yes, 0: no). Religiosity is a dichotomous variable with one for those who reported “not at all religious” and 0 otherwise.

3.3 Age-Period-Cohort Models

By identifying birth cohorts and interview years, we can cross-classify the respondents by cohorts and periods that allows between-cell comparison at the second level and within-cell comparison at the individual level (Yang & Land, 2008, 2013; Yang et al., 2008). Table 1 shows this cross-classify pattern. The 19,364 respondents are nested within 16 birth cohorts and 9 survey years.

An age-period-cohort cross-classified random effect model (HAPC-CCREM hereafter) is necessary for the cohort size analysis (O’Brien, 2014, 2017; Raudenbush & Bryk, 2002). This is not only because respondents in a repeated cross-sectional sample are nested in cells of identical birth cohorts and survey years that share similar random error components unique to their period and cohort, but also because cohort size is a characteristic of aggregated groups rather than individuals (Yang, 2008; Yang & Land 2006, 2013). The HAPC-CCREM also allows random variance across cohort and period groups, which estimates the total amount of cohort and period disparities in happiness and produces a unique best fitting solution (Yang & Land, 2013).

We formulate a series of multilevel cross-classified models with random cohort and period effects. These models allow us to simultaneously estimate the effects of age, period, and cohort variables on happiness (Yang, 2006; Yang et al., 2008; Yang & Land 2006; 2013; Reither 2015). After estimating a series of models with individual- and cohort-level variables, we gauge changes in the variance and random cohort and survey year effects. Therefore, we ascertain which variables account for the cohort dynamics by reducing the size of the random effects. Based on the HAPC-CCREM specification, certain constraints are to be made (Luo & Hodges, 2020b; Luo, 2013; O'Brien, 2017) The linear components and the random intercepts are assumed to be zero. Therefore, we assume happiness does not *linearly* vary across birth cohorts or interview waves.

The model has two components: the "within-cell" and "between-cell." The "within-cell," or individual model, can be expressed as the following:

$$\eta_{ijk} = \pi_{0jk} + \sum_{i=1}^{2} \pi_{ijk} * Age + \sum_{i=3}^{6} \pi_{ijk} * Dem + \sum_{i=7}^{14} \pi_{ijk} * SES + \sum_{i=15}^{19} \pi_{ijk} * Mar + \sum_{i=20}^{23} \pi_{ijk} * Soc + \varepsilon_{ijk} \tag{1}$$

Since the dependent variables are dichotomous, we use $\eta_{\text{ijk}} = \ln \frac{\phi_{ijk}}{1-\phi_{ijk}}$ the left-hand side of the equation, the log of odds of being in the category of being happy for individual *I* in birth cohort *j* and survey year *k*. π_{0jk} is the intercept. π_{1jk} and π_{2jk} are coefficients for age and age squared. π_{3jk} to π_{6jk} are coefficients for four demographic variables of gender, race, nativity, and religiosity. π_{7jk} to π_{14jk} are coefficients for seven SES measures of income, education, and employment. π_{15jk} to π_{19jk} are coefficients for five measures of marital status. π_{20jk} to π_{23} are coefficients for four measures of sociality. ε_{ijk} represents the individual-level residuals.

Individuals' sense of happiness varies by cohort and survey year at cell level. We specify the "between-cell" average cohort size effect as fixed effects and cohort and survey variation as random-effects. The intercept π_{0jk} or the "between-cell" model in Eq. (1) is expressed as:

$$\pi_{0jk} = \theta_0 + \gamma_{01} * ACS + b_{0j} + c_{0k} \tag{2}$$

where θ_0 is the cell-level intercept or the grand mean across all cells, γ_{01} is the coefficient for the cohort-level variable average cohort size, and b_{0j} and c_{0k} are residuals or random effects of cohort and survey year respectively. We estimated these HAPC models in HLM 8 (Raudenbush & Bryk, 2002).

The first concern over HAPC-CCREM is that researchers should theoretically and substantively justify which APC variables should be treated as random effects (or constrained) (O'Brien, 2017). There are theoretical reasons for cross-classifying cohort and period effects as random effects. Firstly, previous studies theorize cohort patterns in happiness as non-linear (Easterlin, 1987, 2010; Economic & Social Research Council, 2015; Pampel & Peters, 1995). Cohort variance has a cyclical pattern that does not monotonically increase or decrease with age. Cohorts are not becoming more or less happy monotonically over birth times; instead, cohort happiness fluctuates with cohort size. This non-linear pattern makes the treatment of cohort as a random effect appropriate. When the association between cohort variable and the outcome is non-linear, HAPC modeling performs remarkably well (Reither, 2015). Secondly, there is no indication that a country's happiness intrinsically increases or decreases over time (Bardo et al., 2017). Economic growth—a typical period effect—and happiness are not correlated over a long period (Easterlin, 2004, 2015). Cohort and period are "arbitrary" properties of historical events and survey design. For example, events such as World Wars or pandemics incurred during birth years or interview years are generally "random" or unpredictable with survey information, thus cohort and period effects can be estimated as random residuals.

The second concern of HAPC-CCREM is that the model intrinsically shrinks one of the two random effect variables (cohort or period) to near zero, thus underestimating this effect (Luo & Hodges, 2020b; O'Brien, 2017). Ekstam (2021) suggests we can see which variable is more likely to be affected by shrinkage in the HAPC-CCREM by comparing the correlation between age and cohort and the correlation between age and period. The data shows our HAPC-CCREM are more likely to underestimate cohort effect (correlation with age = −0.959) than the period effect (correlation with age = 0.076).

Even though the period effect is less likely to be affected by shrinkage, period effects on happiness may be intrinsically small (Ekstam, 2021). Little evidence supports that *long-term* economic and cultural trends change a population's overall happiness (Bardo et al., 2017; Easterlin, 2015). A repeated cross-sectional study also shows that period effect has limited effect on happiness—economic crises may have a positive effect on happiness because "people feel the need for staying close together to deal with the consequences of the crises" (Gudmundsdottir, 2013, p. 1098). Based on these reasonings, the chance that HAPC-CCREM artificially underestimates the period effect or overestimates the cohort effect is unlikely.

Because we delineate birth cohorts in meaningful ways, use survey years to capture historical dynamics, addressing implicit constraints with theoretical/substantive justification, and do not attempt to find "solutions" to the APC identification, these estimates are not undermined by the concerns over HAPC-CCREM models (Luo & Hodges, 2020b; Luo, 2013; O'Brien, 2017).

To evaluate results from the HAPC-CCREM models, we also estimate two-level models that include the age effect at the first level and cohort effect at the second level but not the period effect. We cluster individuals within the 16 birth cohorts at the second level. The number of A, P, and C groups and assumptions about which A, P, C group to be constrained significantly affect estimates in the HAPC-CCREM models (Bell & Jones, 2018; Luo & Hodges, 2020a, 2020b; O'Brien, 2017). These reduced models avoid the age-period-cohort identification problem by dropping the period effect, assuming the period is small or partially confounded with cohort or age effects (Bell & Jones, 2018; Luo & Hodges, 2020b).

Our analysis has three steps. First, we report descriptive statistics of the analytic sample across generations. Next, we use the nested regression approach and employ the HAPC model to test the relative cohort size hypothesis and see if any individual-level variables will account for the cohort size effect. Lastly, we present graphs to illustrate the changes in cohort residuals for each model. These graphs demonstrate how ACS, demographic variables, SES, marital status, and sociality contribute to the cohort differences in happiness.

4 Results

4.1 Generational Differences in Happiness, SES, Marital Status, and Sociality

Boomers are the unhappiest generation with 83.1% of respondents reporting happiness. Table 2 presents the unweighted descriptive characteristics of the ESS UK (2002–2018) as well as population statistics from the Office of National Statistics (2017) for each generation. The youngest and the oldest generations are the happiest. Generation Z (Gen

Table 2 Unweighted Descriptive Statistics by Generations (European Social Survey—UK 2002–2018)

	The Greatest[a] 1900–1927	The Silent 1928–1945	Baby Boomers 1946–1964	Gen X 1965–1980	Millennials 1981–1996	Gen Z 1997–2012	Total
% Happy (> 5 on the scale)	88	87.6	83.1	83.4	86.9	89.8	85
Average cohort size (millions)	0.99	0.75	0.88	0.83	0.76	0.74	0.84
Age	84	72	55	38	25	17	50
% Female	59	54.7	52.9	56.7	57.3	46.8	55.2
% Minority	1.5	3.2	5.8	10.3	11.6	8.8	7.2
% Foreign Born	6.5	6.7	9	14.6	15.3	9.3	10.8
% Not Religious	7.2	10.3	16.7	24.5	29.8	30.1	19.2
% Married	23.8	29.3	29.2	25.8	4.7	0.5	24.1
% Single	6.1	5.9	12.3	34.3	77.4	99.5	27.3
% Separated	0.1	0.8	2.5	2.2	0.8	0	1.7
% Divorced	4.4	12	19.2	10.2	1.2	0	11.7
% Widowed	61	30	5.8	0.7	0.3	0	11
% Marital N/A	4.6	22	31	26.8	15.6	0	24.2
% Lower Income Class	43.7	43.2	28.9	24	31.1	26.9	31.5
% Middle Income Class	25	26.6	33	36.1	29.4	13.4	31.4
% Upper Income Class	4.4	7.5	24	29.6	15.4	5.6	19.7
% Income N/A	27	22.7	14.1	10.3	24.1	54.2	17.4
% Less than HS	61.6	48	19.5	7.6	8.7	15.7	22.5
% High School	19.5	21.7	32.3	28.5	29.4	43.5	28.2
% Some College	10.3	13.9	20	26.5	31.2	37	21.9
% College	6	10.8	18.4	25.3	24.2	2.8	18.8
% Advance	2.7	5.5	9.9	12.2	6.5	0.9	8.7
% Unemployment	0	0.6	4.3	6.1	9.8	6.5	4.7
% Rarely/Never Socialize	12	9.1	11.1	10.5	5.8	1.9	9.7
% Socialize Monthly	16.3	19.7	26.9	27.7	18.5	13.4	23.7
% Socialize Weekly	20.4	19.8	22.8	23.3	18.4	12	21.4

Table 2 (continued)

	The Greatest[a] 1900–1927	The Silent 1928–1945	Baby Boomers 1946–1964	Gen X 1965–1980	Millennials 1981–1996	Gen Z 1997–2012	Total
% Socialize > 1 a Week	36.1	37.7	28.4	26.6	31.3	37	30.7
% Socialize Everyday	15	13.7	10.7	11.9	26	35.7	14.5
Sample Size	866	4,009	6,236	5,097	2,940	216	19,364

[a]The Greatest generation includes cases from pre-1900

Z) is the happiest generation (89.8% are happy) while the Greatest Generation is the second happiest (88% are happy). Millennials and the Silent generation are less happy with similar happiness levels of 86.9% and 87.6% respectively. The Greatest generation has the highest average cohort size at 0.99 million new births per year while the boomer generation has the second largest average cohort size of 0.88 million per year, followed by Gen Xers of 0.83 million per year. The average cohort size for Millennials and the Silent generation are similar, at 0.76 million and 0.75 million per year respectively. The youngest generation, Gen Z, is the smallest of 0.74 million new births per year.

Boomers are among the more well-off generations based on the three measures of SES. The distribution of lower-income is U-shaped, with those from the older generations (before Boomers) and the youngest generation (Millennials) clustering in the lower-income class. About a third of respondents from Gen X (36.1%) and the Baby Boomers (33%) considered themselves middle class (people who earn at least 27 thousand Euros a year), and about a quarter of respondents from these two generations considered themselves with upper income (people who earn more than 60 thousand Euros). 17.4% of respondents did not report income class. The proportion of people who did not report income has an inverted U-shaped distribution across generations with the older and younger cohorts more likely to report unknown income than the Boomers and Gen Xers. The majority of Boomers (57%) consider themselves in the middle- and upper-income categories, only outnumbered by Gen X at 65.7%. As for education, Gen X has the highest number of college graduates and the lowest number of those who did not finish high school. Older generations generally have lower educational attainment—the Greatest and the Silent have 61.6% and 48% of respondents did not finish high school, respectively, compared to only 19.5% and 7.6% for Boomers and Gen X, respectively. Gen X has the highest number of college graduates (25.3%) and advanced degree holders (12.2%). Millennials have the highest unemployment rates (9.8%), trailing by Gen Z (6.5%), Gen X (6.1%), and Boomers (4.3%). The unemployment rates for the Greatest and the Silent are near 0% because most of them have reached retirement age and be out of the labor force. Overall, on these measures of SES, the Boomers are in a fairly advantageous position. Among the six generations, they rank second in income, third in education, and have the lowest unemployment rate among the four generations active in the labor force.

Boomers have the highest rates of separation and divorce of all generations. The Silent generation has the highest number of married (29.3%) followed closely by Boomers (29.2%). Boomers also have the highest separated rate (2.5%) and divorced rate (19.2%). The Greatest have the highest widowed rate (61%) due to their advanced age. The three younger generations have higher proportions of those who are single with the Gen Z having the highest (99.5%) followed by millennials (77.4%) and Gen X (34.3%). Because a substantial number of respondents did not report marital status (24.2%), the actual distribution of marital status for each generation is undetermined.

Boomers rank the last in sociality. Boomers are the least likely to socialize every day (the highest frequency category) with only 10.7% reporting doing so, lower than the two oldest generations of the Greatest (15%) and the Silent (13.7%). More than a third of Gen Z (35.7%) socialize every day, trailing by millennials (26%). Boomers also have the second lowest rate of socializing more than once a week (second highest frequency category) of 28.4% only slightly higher than the lowest of Gen X at 26.6%. This is rather surprising, as the Boomers tend to have more peers than members of other generations.

Table 3 Odds Ratios for Being Happy using Hierarchical Age Period Cohort Cross-Classified Random Effect Models with Adjusted Population Weight (European Social Survey—UK 2002–2018, N = 19,364)

	Model A	Model B	Model C	Model D	Model E	Model F
Fixed Effects						
Cohort-Level						
Average Cohort size (millions)		0.237*	0.229*	0.163*	0.152**	0.197**
Individual-Level Variables						
Demographics						
Age	0.985	0.995	0.998	0.982	0.955***	0.976+
Age Squared	1.0002*	1.0001	1.0001	1.0004***	1.0006***	1.0004***
Female			0.894*	0.934	0.991	0.988
Minority			0.621***	0.633***	0.625***	0.644***
Foreign Born			1.248*	1.282**	1.219*	1.237*
Not Religious			0.739***	0.755***	0.78***	0.8***
Income Class (Reference = Lower)						
Middle Class				1.889***	1.68***	1.671***
Upper Class				3.438***	2.862***	2.742***
Income N/A				1.339***	1.187***	1.176*
Education Level (Reference = less than HS)						
High School				1.199**	1.195**	1.169*
Some College				1.410***	1.406***	1.364***
College				1.828***	1.838***	1.731***
Advanced Degree				1.768***	1.778***	1.638***
Employment Status						
Unemployed				0.503***	0.525***	0.538***
Marital Status (Reference = Married)						
Separated					0.407***	0.384***
Divorced					0.584***	0.564***
Widowed					0.451***	0.41***

Table 3 (continued)

	Model A	Model B	Model C	Model D	Model E	Model F
Single					0.738***	0.692***
Marital N/A					1.306**	1.271**
Sociality (Reference = Never/Rarely)						
Monthly						2.333***
Weekly						2.42***
> 1 a Week						3.392***
Every day						3.392***
Intercept	7.12***	6.815***	6.837***	7.793***	7.535***	7.866***
Random effects: for model A: total variance. for models B—G: % of variance explained relative to Model A						
Cohort Effect (Row)	0.04687***	47.5%***	52.7%***	29%***	52.2%***	60.6%***
Period Effect (Column)	0.00245+	0.098+	0.000*	0.000*	0.000**	0.000*
-2 Log-Likelihood (Total Variance)	13,775.61	13,769.93	13,705.49	13,064.27	12,849.10	12,487.51
Total Variance Explained	–	0.0004	0.0051	0.0516	0.0673	0.0935

*$P < .05$, ** $P < .01$, *** $P < .001$, + $P < 0.10$

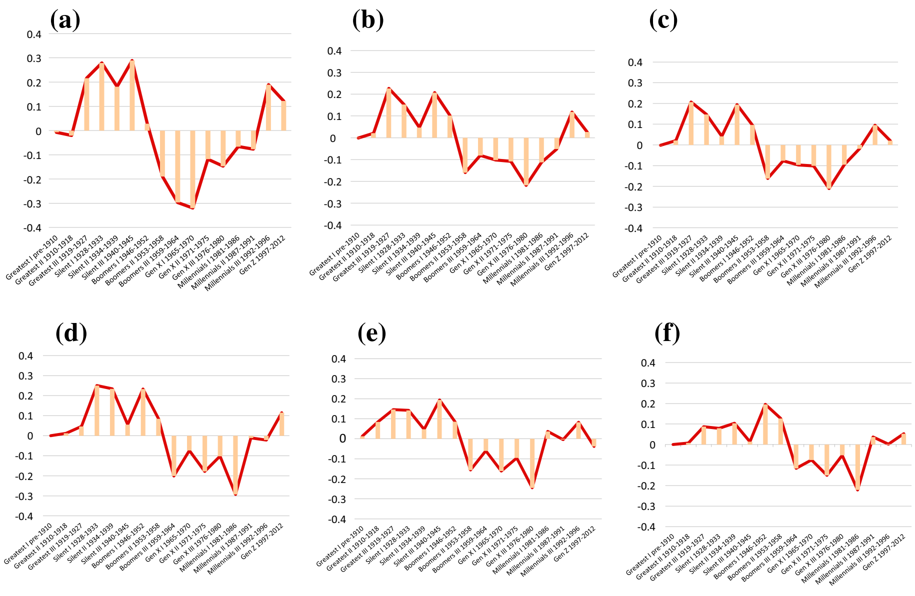

Fig. 1 Cohort variations in hierarchical age period cohort cross-classified random effect models of being happy (ESS UK 2002–2018, $N = 19{,}364$). Proportion of cohort variance unexplained (residuals) in Y-axis and cohort groups in X-axis. (**a**) cohort variance explained 0%; (**b**) cohort variance explained 47.5%; (**c**) cohort variance explained 52.7%; (**d**) cohort variance explained 29%; (**e**) cohort variance explained 52.2%; (**f**) cohort variance explained 60.6%

4.2 Modeling Net Effects of Cohort, SES, Marital Status, and Sociality

To unravel the net effect of cohort size, SES, marital status, and sociality, we estimate a series of nested multilevel cross-classified age-period-cohort random effect models. Table 3 summarizes our findings. Model A is the baseline model that only includes age and age-squared terms at the individual level and cohort identification and interview year at the cell level. The latter models are compared to Model A to see how additional variables explain the variability of cohort-level happiness. We add average cohort size in Model B to illustrate the cumulative effect of cohort size. Model C includes demographic controls—gender, minority status, foreign-born, and religiosity. Model D considers socioeconomic status variables—income class, education level, and employment status—to the previous model. We add marital status to Model E. Model F accounts for sociality and is our full model.

Model A suggests that random errors for cohort group and interview year are significant. In other words, the likelihood of being happy varies substantially across cohorts and periods. Figure 1a is a plot of the cohort residuals in Model A. The bar heights represent unexplained cohort variations with a positive bar suggesting that the cohort's logged odds happiness is higher than predicted and vice versa for a negative bar. Figure 1a shows that Gen X cohort I is the unhappiest, trailing the Baby Boomer cohorts II and III, controlling for age and period effects. Age and age squared terms are not significant. Similar to Yang's findings (2008), the age effects are accounted for by the cohort and the period effects.

Model B shows that the effect of the average cohort size is negative and statistically significant ($p<0.05$) after adjusting for age-period-cohort effects. For each million new live births, the odds of a cohort reporting happiness are 24%. The average cohort size is negatively associated with happiness across all models ($p<0.05$). Members of the cohort born during times of high fertility per year are less likely to be happy. Figure 1b shows that by adding the average cohort size, Model B accounts for almost half of cohort variances in happiness (47.5%, $P<0.001$), indicating strong predicting power of the average cohort size on happiness. Not only does the average cohort size reduce the size of the cohort variance, but it also changes the shape of residuals bars. Compared to Fig. 1a, the negative cohort residuals for the Boomers cohort III (1959–1964) and the Gen X cohort I (1965–1970) are greatly reduced. The "U-shaped" cohort effect pattern among the Boomers and Gen X has almost been flattened. The positive cohort residual for the Silent cohort I (1928–1933) is also reduced. In other words, the below-average happiness among the late Boomers and early Gen X and the above-average happiness among the first Silent cohort can be partly explained by the cohort size. The results are consistent with Hypothesis A - individuals from small cohorts are happier than individuals from larger cohorts.

Model C accounts for social and demographic control variables—gender, minority status, foreign-born status, and religiosity, in addition to Model B. This model explains an additional 5.2% variance pushing the total cohort variance accounted for to 52.7% ($P<0.001$). The negative cohort size effect remains statistically significant ($P<0.05$). Model C shows that female respondents are 10.6% less likely to report being happy than males ($P<0.05$). Racial minorities are 37.9% ($P<0.001$) less likely to report being happy than non-minorities. Foreign-borns are 1.25 times ($P<0.05$) more likely to report being happy than native-born. Non-religious people are 26.1% ($P<0.001$) less likely to say they are happy than religious ones. In Fig. 1c, the cohort effect residuals pattern remains approximately the same, affirming Hypothesis A.

Model D through F include a series of individual-level predictors. In Model D, the addition of the socioeconomic status variable reduces the percentage of cohort-level variance explained down to 29%. The significant average cohort size effect ($P<0.01$) suggests that socioeconomic factors such as income, education, and employment status not only do not add any explained cohort variance in happiness but also inflate the cohort-level variance accounted. The reduction in variance explained implies that the positive SES effect on happiness does not apply to certain high SES cohorts that are "supposed" to be happy. The fact that Baby boomers are better off in SES than other cohorts contradicts their unhappiness. Therefore, the parameter estimates for SES conflates the cohort variance. We thus reject Hypothesis B, that SES measures account for the negative association between cohort size and happiness.

Model E adds measures of marital status. This addition accounts for an additional 13.2% of the cohort-level variance, which explains 52.2% of total variance ($P<0.001$). Those who are married are 59.3, 31.6, 54.9, and 26.2% happier than those who are separated, divorced, widowed, or single, respectively ($P<0.001$). Figure 1e shows the size of the cohort residual is further reduced, though the overall cohort residuals pattern remains the same. This lends support for Hypothesis C that members of larger cohorts are more likely to divorce and separate than smaller cohorts, thus are less happy than members of smaller cohorts.

In Model F, we add the sociality measure—frequency of socializing with friends, relatives, and colleagues. The negative cohort size effect ($P<0.01$) and all the sociality variables are significant ($P<0.001$). For example, those who socialize monthly are 2.33 times happier than those who never socialize. The negative association between cohort size and

Table 4 Odds ratios for being happy using multi-level modeling with 16 cohort groups at 2nd level and with adjusted population weight (European Social Survey—UK 2002–2018, $N = 19{,}364$)

	Model A	Model B	Model C	Model D	Model E	Model F
Fixed effects						
Cohort-Level		0.411**	0.399**	0.166**	0.267***	0.366*
Average Cohort size (millions)						
Individual-Level Variables						
Demographics						
Age	0.964***	1.003*	1.002	1.011***	1.010***	1.011***
Age Squared	1.0004***	1.0003***	1.0003***	1.001***	1.001***	1.001***
Female			0.876**	0.931 +	0.995	0.985
Minority			0.653***	0.668***	0.655***	0.685***
Foreign Born			1.300***	1.299**	1.228**	1.268**
Not Religious			0.759***	0.777***	0.787***	0.816***
Income Class (Reference = Lower)						
Middle Class				1.927***	1.714***	1.692***
Upper Class				3.668***	3.020***	2.84***
Income N/A				1.294***	1.145*	1.136*
Education Level (Reference = less than HS)						
High School				1.294***	1.214**	1.186**
Some College				1.233***	1.455***	1.422***
College				1.878***	1.834***	1.733***
Advanced Degree				1.766***	1.724***	1.607***
Employment Status						
Unemployed				0.537***	0.556***	0.552***
Marital Status (Reference = Married)						
Separated					0.436***	0.406***
Divorced					0.583***	0.560***
Widowed					0.470***	0.424***
Single					0.734***	0.686***
Marital N/A					1.362***	1.378***
Sociality (Reference = Never/Rarely)						
Monthly						2.416***
Weekly						2.417***
> 1 a Week						3.670***
Every day						3.660***
Intercept	4.998***	10.546***	12.391***	11.578***	9.474***	3.166**
Random effects: for model A: total variance. For models B—G: proportion of variance explained for relative to model A						
Cohort Effect	0.0833*	0.306	0.316	−0.701	−0.305	0.025
−2 Log-Likelihood	16,327.22	16,320.9	16,257	15,513.42	15,260.9	14,861.44
Total Variance Explained	–	0.0004	0.0043	0.0498	0.0653	0.0898

$^{*}P < .05$, $^{**}P < .01$, $^{***}P < .001$, $^{+}P < 0.1$

happiness remains significant; for every million increases in cohort size, the odds of being happy is reduced by 80.3% ($P<0.05$). Model F accounts for 60.6% of a cohort effect and increases the variance explained by 8.4%. We reject Hypothesis D that members of large cohorts socialize more and that frequency of socializing is responsible for the link between cohort size and happiness.

Table 4 illustrates the odds ratios for the two-level (or reduced) model with 16 cohorts at the second level. By dropping the period groups at level-2 to avoid identification problems, we demonstrate whether results from Table 3 remain robust. All results in these two-level models, except for age effects, are virtually identical to that of the HAPC-CCRM models. The age effect is u-shaped in the base model. The average cohort size effects are negative and significant across all reduced models. The fixed effects for all the confounding variables (SES, marital status, and sociality) are identical to those in Table 3 in statistical significance and direction of effect. The pattern of cohort variance explained in the reduced models is the same as in Table 3. Both sets of models illustrate that SES variables inflate the cohort variance, whereas marital status and sociality variables reduce the cohort variance, thus contributing to cohort-based variations in happiness.

5 Conclusion and Discussion

We have analyzed the effects of cohort size, SES, marital status, and sociality on happiness using repeated national samples from nine waves of the United Kingdom Subset of the European Social Survey 2002–2018 ($N=19$, 364). Through a series of hierarchical age-period-cohort cross-classified models, we found that the largest cohorts are the least happy in the British data. Our models consistently verify a negative cohort size effect, which supports Hypothesis A that individuals from smaller birth cohorts tend to be happier than those of large birth cohorts. The effects of cohort size on happiness remain statistically significant in all models after controlling for demographic characteristics, SES, marital status, and sociality. These individual-level characteristics cannot fully account for the cohort-specific variations in happiness. The number of people born in specific cohorts influences the self-evaluation of their happiness net of age-period effects, individual economic conditions, marital status, sociality, and demographic controls. In particular, the Baby boomers report the lowest level of happiness compared to other cohorts, consistent with findings in Yang's (2008) and Fukuda's (2013) studies. This study provides evidence that such a negative relationship between cohort size and happiness is not limited to the U.S. experience.

Average cohort size is by far the most important variable in accounting for cohort variance in happiness. Almost half of the difference in happiness among cohorts is due to cohort size. Cohort size accounts for 48% of the variation in happiness, responsible for the largest variance among all variables we explored in this study. This impact of cohort size is above and beyond SES, marital, and sociality factors we analyzed in our models. Being a member of a large birth cohort depresses happiness by exerting a direct psychological effect on the evaluation of the quality of life. This sense of heightened stress and intense competition is labeled a *Crowding Mechanism* that is predominantly psychological (Easterlin, 1987, 2010). Individuals of large cohorts perceive crowdedness as potential competition and experience more psychological stress, regardless of their actual economic situation. Members of large cohorts have more peers as a reference group to form the basis of comparison. Exposure to numerous successful peers may trigger a sense of defeat and disappointment among boomers than people of smaller cohorts who compare against fewer successful peers.

Marital status is the second most important factor in accounting for cohort variations in happiness. The model with marital status explains an additional 13% of cohort variance in happiness. The Boomer generation is the most likely to have experienced separation and divorce of all generations and less likely to be ever married than the two older generations.

The frequency of meeting with friends, relatives, and colleagues also contributes to cohort variations in happiness. Measures of sociality are responsible for an additional 8% of the cohort variance in happiness. Despite having the highest number of peers and siblings, the boomers socialize the least. Members of the crowded cohort are also the loneliest and gloomiest. The boomers are the loneliest generation despite growing up with large peers and siblings as they face more competition in the family, schools, and workplace (Macunovich & Easterlin, 2010). This life-long experience of contesting among peers incurs a sense of exclusion and alienation rather than collaboration, companionship, and socialization among peers. Members of the most populous cohort are "lonely in a crowd." This societal disconnection, in turn, further contributes to their unhappiness.

Contrary to the predictions that economic wellbeing such as income and employment leads to more happiness (Easterlin, 2001, 2004) and that the cohort with these resources are more likely to be happier than those without, the Boomers are the gloomiest even with an abundance of material resources. After considering the positive effects of higher socioeconomic attainments and status of the Boomers, the negative cohort effect is even more accentuated. Boomers have achieved higher income, more college degrees, and are less likely to be unemployed than most cohorts, yet they remain the least happy even with these material benefits. These results suggest a negative effect of large cohort size on happiness is not through an economic mechanism of material deprivation. Rather, cohort-size studies need to consider a socio-psychological process (Macunovich & Easterlin, 2010). It is the disintegration from peers, friends, and family, not suffering from lower SES as hypothesized by Easterlin, that is likely the culprit of unhappiness among the Boomers.

Grounded on Easterlin's Cohort Size Hypothesis and existing empirical evidence on happiness, we have estimated a series of hierarchical age-cohort-period cross-classified random effect models, treating cohort and period as random effects. We have also followed suggestions (O'Brien et al., 2008, Luo & Hodges, 2020a; Ekstam, 2021) to improve the robustness of our HAPC-CCREM by estimating a series of two-level models that include the age effect at the first level and cohort effect at the second level but not the period effect. These models with age fixed effect and cohort random effect have replicated all empirical patterns in the HAPC-CCREM models. We have presented results from HAPC-CCREM models as they are superior to the reduced two-level models in providing better goodness of fit, i.e., a more accurate estimate of cohort variance, and in isolating noises from period effect. Since all APC components can have significant and independent effects on social outcomes, models that drop one aspect of APC effects are misspecified (O'Brien et al., 2008).

Our study contributes to the methodological debate raised by Luo (2013) and Bell and Jones (2018). Although HAPC-CCREM can statistically (or artificially) disentangles age, cohort, and period effects (Luo & Hodges, 2020a), the mathematical "manipulation" proposed by Yang and Land (2013) allows age, period, or cohort to be independent of the other two factors (O'Brien et al., 2008; Luo, 2013). In this study, we theorize that the cohort size effect is a unique effect independent of the aging process and historical times. This cohort effect that a larger cohort size negatively affects subjective wellbeing is perceived as robust and independent of age and period, evidenced by consistent findings of such a cohort effect from the United States (Yang & Land, 2013), China (Shu & Ye, forthcoming), and the United Kingdom who came of age at different historical times. However, this assumption of HAPC-CCREM that cohort effects can occur independently or additively of age and period effects could be challenged. An alternative approach is to view cohort as embedded in the age-period specification (Luo & Hodges, 2020a; Ryder, 1965) and can be expressed as a mix of effects of age and period and their interactions. Future research needs to evaluate under which circumstances cohort effects could be perceived as independent and additive and in what ways cohort effects are age-period interactions as well as the implications of these decisions on modeling choice and approaches.

We shed some light on the paradox of the Baby Boomer generation. On the one hand, they have experienced substantial economic gains, better off in income, education, and occupation than most cohorts. On the other hand, the Baby Boomer generation is some of the most unhappy, lonely, depressed, and suicidal cohorts in the U.K and the U.S as well (McCarthy, 2015; Flowers et al., 2017). The experience of growing up in a crowded world constantly fighting for a share has led to alienation and disintegration from peers, friends, and family. These disconnections are likely to lead to unhappiness. The baby boomers are perpetually locked into their life experiences of crowding, as Economist H. Scott Gordon (1977, as cited in Easterlin, 1987, p. 31) stated, “These poor souls came into a crowded world… There was crowding in the maternity wards…; there was crowding in the kindergarten classes…; there will be crowding in the universities…; crowding in the search for jobs and housing… and so on until there crowding in the funeral parlors and the cemeteries.”

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Availability of Data and Material The datasets used in this study are available in the European Social Survey, https://www.europeansocialsurvey.org/about/country/united_kingdom/ess_united_kingdom.html.

Code Availability We used Stata 15 and HLM 8 for statistical analysis. Stata do-file is available upon request.

Declarations

Conflict of interest To the best of our knowledge, the two authors have no conflict of interest, financial or otherwise.

Consent to Participate Not applicable.

Consent for Publication Yes.

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