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Age-Period-Cohort Models

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Synonyms

Age-period-cohort analysis; Age-period-cohort conundrum; Age-period-cohort identification problem; Cohort analysis

Definition

Age-period-cohort (APC) models broadly refer to statistical techniques used to isolate the effects of chronological age (i.e., age effects), societal conditions at the time of observation (i.e., period effects), and experiences shared among individuals in the same historical moment (i.e., cohort effects) – "shared experiences" are sometimes specific (e.g., graduation from high school, military service, marriage, etc.), but demographers and social scientists typically operationalize cohort in more general terms (i.e., birth cohort). Aging scholars use APC models to understand how age, period, and cohort effects influence a range of health and socioeconomic outcomes that are evaluated through either longitudinal or repeated cross-sectional data.

Overview

Since the mid-1960s, social scientists have articulated the importance of separating three temporal dimensions – age, period, and cohort – as each makes unique contributions to the attitudes, beliefs, and well-being of individuals (Riley 1973; Ryder 1965). To elucidate this point, the current entry draws on a subjective well-being (i.e., happiness) literature that examines how happiness (a) changes across the life course (age effects), (b) varies across points of observation (period effects), and (c) is affected by experiences shared among people born at the same time (cohort effects). While all three temporal dimensions affect happiness, each is conceptually distinct (see George 2010 for further details).

Age effects reflect physiological and developmental changes due to biological and social processes of aging. Given common age-related declines in health and losses of important social roles and relationships, happiness was traditionally hypothesized to decrease across the life course. However, happiness has more recently been shown to actually increase with age – likely because as people age, they tend to invest more in emotionally meaningful aspects of life (Bardo 2017).

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Period effects encompass complex macro-level social, political, economic, and environmental conditions that characterize the period during which an outcome of interest is measured. Happiness levels among people of all ages generally decrease during periods of high inflation and unemployment and increase after conditions improve (Bardo et al. 2017). While period effects often ebb and flow, they can also be more permanent in nature. For example, long-term increases in happiness may occur among people in developing nations that experience steady social and economic progress over time.

Cohort effects reflect life experiences and circumstances shared among people born in the same calendar year or during a particular historical episode (e.g., World War II). Each birth cohort is unique, as only one birth cohort can encounter the same sociohistorical landscape at approximately the same age (Ryder 1965). For example, scholars have argued that persons born during the Great Depression are happier than others because they assess current happiness in contrast to formative experiences characterized by deprivation (Elder 1974). Conversely, the Boomer cohort is understood to be less happy than other cohorts because of its large size, which led to increased competition for resources (Easterlin 1980).

Given the distinct conceptual nature of each temporal dimension, the identification of APC effects in quantitative data analysis may seem like it should be a simple task. However, it is impossible to separate APC effects in statistical models without the use of important assumptions, which either pertain to data characteristics or a priori knowledge about one of the three temporal dimensions (Reither et al. 2015a, b). Without these assumptions, scholars cannot estimate APC models due to the *identification problem* – i.e., the fact that each temporal dimension is a linear function of the others (Glenn 2005). For instance, if a 50-year-old respondent (age) completed a survey in 2000 (period), then s/he must have been born in 1950 (i.e., cohort = period – age). In the presence of exact linear functions, traditional statistical techniques such as ordinary least squares regression models fail. However, different approaches to disentangle APC effects have been developed and discussed in a long line of population aging literature that date back to at least the 1960s.

Key Research Findings

Norman Ryder (1965) emphasized how birth cohorts drive social change, providing the theoretical rationale for APC analysis. Four years later, Peter Uhlenberg (1969) proposed one of the first APC models, which required qualitative interpretation of graphical data. Matilda White Riley's (1973) foundational work was among the first to document and discuss APC-related statistical and methodological issues. Around the same time, Glen Elder's (1974) widely-acclaimed *Children of the Great Depression* highlighted the need for more cohort studies in the social sciences.

Norval Glenn (1977) wrote the first comprehensive guide to cohort analysis. Although an updated edition was not published for more than a quarter century (Glenn 2005), there were continued efforts to advance APC techniques that are worth noting. For example, Erdman Palmore (1978) argued that three fundamental differences must be addressed to advance APC research: (a) earlier and later measurement of the same cohort (i.e., longitudinal differences), (b) measurement among younger and older cohorts at a single point in time (i.e., cross-sectional differences), and (c) older cohorts at earlier measurement and younger cohorts at later measurement who became the same age as older cohorts at the earlier measurement (i.e., time-lag differences).

Demographers have pointed out flaws in APC techniques that were commonly used in the 1970s, as well as promising areas for advancement (Hobcraft et al. 1982; Reither et al. 2015a). For example, Mason et al. (1973) wrote a seminal article on APC methods, showing how to address the identification problem by (a) measuring age, period, and cohort effects with a series of dummy variables, and (b) forcing at least two of these effects to be equal. For example, a scholar might force the 1930 birth cohort to have the same effect on an outcome (e.g., happiness) as the 1931 birth cohort. This "breaks" the linear APC dependency, allowing traditional statistical models to yield estimates. However, this method assumes that the equality constraint has no (or only very little) effect on the outcome of interest. In practice, this assumption is often violated, leading to unreliable estimates of APC effects.

Throughout the 1980s, researchers continued to develop new APC techniques, but with mixed success. For example, a proxy-variable model that replaces age, period, or cohort with an alternative measure that adequately explains an omitted time dimension was proposed (Heckman and Robb 1985), but this technique is problematic because each time dimension embodies contemporaneous influences. In other words, a proxy substitute for one of the three dimensions is likely not adequate. For example, period is often substituted with macroeconomic variables, but it is generally overly parsimonious to assume that macroeconomic circumstances sufficiently reflect the totality of period effects (Fukuda 2010).

The APC characteristic model attempted to minimize the assumptions required by extant approaches (e.g., proxy-variable model) by replacing birth year with cohort-specific characteristics (e.g., birth cohort size and the demographic makeup of specific birth cohorts) (O'Brien 1989, 2000). However, the selection of such characteristics is often not justifiable given a lack of prior knowledge. The orthogonal period-effect model (Deaton and Paxson 1994), building on the cohort characteristic model, implements constraints on period through identifying macroeconomic effects that affect both age and cohort, but this too requires strong assumptions in replacing period with macroeconomic effects.

In sum, the best techniques rely on methods that are based on minimal assumptions and estimable functions (Robertson et al. 1999). One such approach is the cross-classified random-effects model, which addresses the APC identification problem presented in repeated cross-sectional survey data via a hierarchical modeling strategy where one dimension of time is treated as fixed and the other two are included in the random effects portion of the model (Yang and Land 2006).

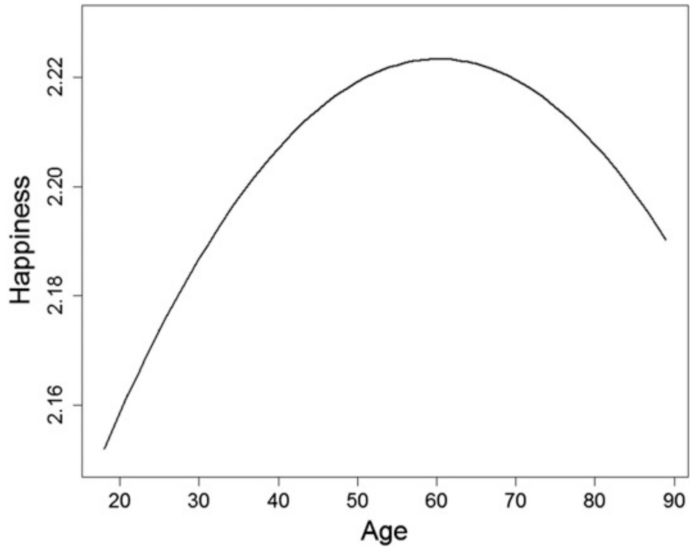
Examples of Application

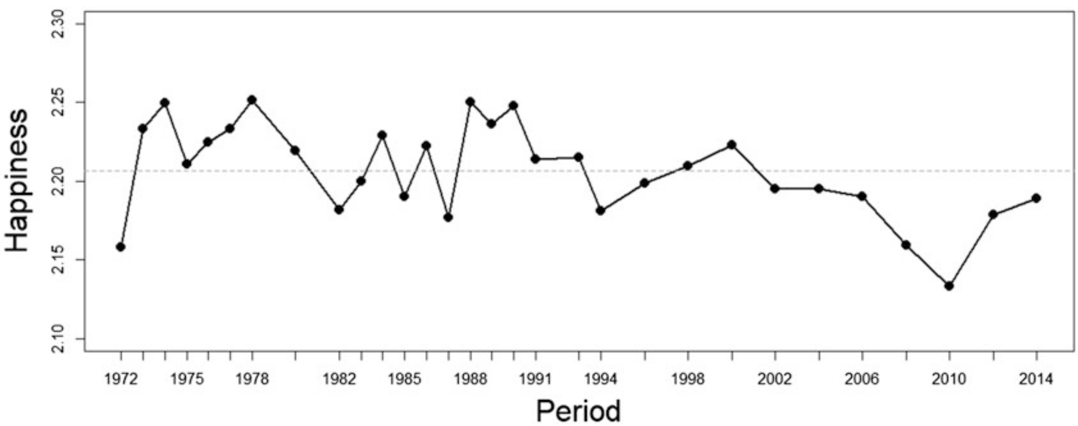
Aging scholars are interested in understanding how happiness is patterned across the life course, whether average happiness levels have changed over time, and if birth cohorts share unique circumstances that differentially shape perceived quality of life. Answers to such questions require data that span a long period of time and include respondents who were born in different years but observed at the same ages across the adult life course. Using data from the General Social Survey (GSS, 1972–2004), Yang (2008) demonstrated that (a) happiness in adulthood increases until the mid-to-late 60s when it begins to decline, (b) aggregate happiness levels have fluctuated only slightly across time, and (c) the Boomers are substantially less happy than any other birth cohort. The present example extends Yang's (2008) study by using five more recent waves of GSS data that span an additional 10 years (i.e., 1972–2014).

Results from cross-classified random-effects APC models show that, similar to Yang (2008), happiness increases with age until the mid-to-late 60s when it begins to decline (see Fig. 1). Also similar to Yang (2008), happiness fluctuates only slightly between 1972 and 2004, after accounting for age and cohort effects (see Fig. 2). However, analyses of these more recent data reveal strong period effects that coincide with the Great Recession (i.e., 2008–2010). Finally, and also comparable to Yang (2008), the Boomers (those born 1945–1964) are substantially less happy than any other birth cohort (see Fig. 3).

The present findings are useful for showing how aggregate happiness levels have changed since Yang's (2008) study, and that the Boomers continue to be the only unique cohort. Present findings also provide support for an inverse J-shaped age pattern in happiness. However, what these findings cannot tell us is whether the age pattern in happiness has changed over time. This question is important to consider because some scholars contend that recent shifts in American culture have led to the idealization of goals that young adults are currently unable to obtain, which has resulted in decreased happiness around

Age-Period-Cohort Models, Fig. 1 Age pattern in happiness: Cross-classified random-effects model

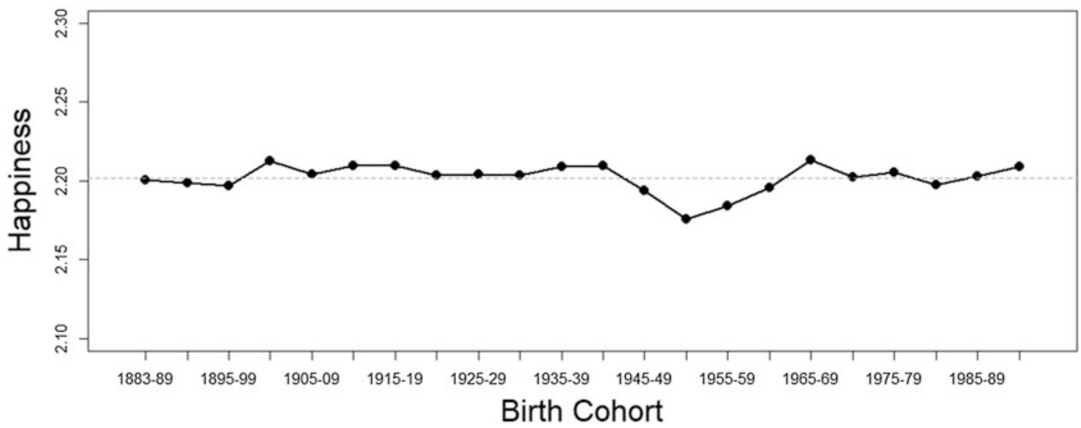




Age-Period-Cohort Models, Fig. 2 Period pattern in happiness: Cross-classified random-effects model

age 30 (Twenge et al. 2016). While the present results, at least in comparison to Yang (2008), may appear to imply the contrary (i.e., the age-happiness pattern has remained constant), Fig. 1 simply depicts the "average" age pattern observed over this 43-year period, net of period, and cohort effects. In other words, conclusions as to whether the age-happiness pattern has remained unchanged cannot be drawn from these analyses (Bardo et al. 2017).

A dummy variable modeling approach was used to examine the underlying trend in the age-happiness pattern. This APC technique is generally only useful when the omitted time dimension assumption can be met (i.e., either age, period, or cohort are not associated with the outcome of interest). Given a priori knowledge from well-established theory (i.e., the Boomers are the only distinct cohort), those born between 1945 and 1964 can simply be excluded from models that include age and period but omit cohort. However, this approach would require 60 interaction terms: 30 wave $\times$ age terms and 30 wave $\times$ age^2 terms (to capture a nonlinear age-happiness pattern). Thus, rather than relying on this approach that would be computationally complex, an adapted version of the dummy variable approach was used.



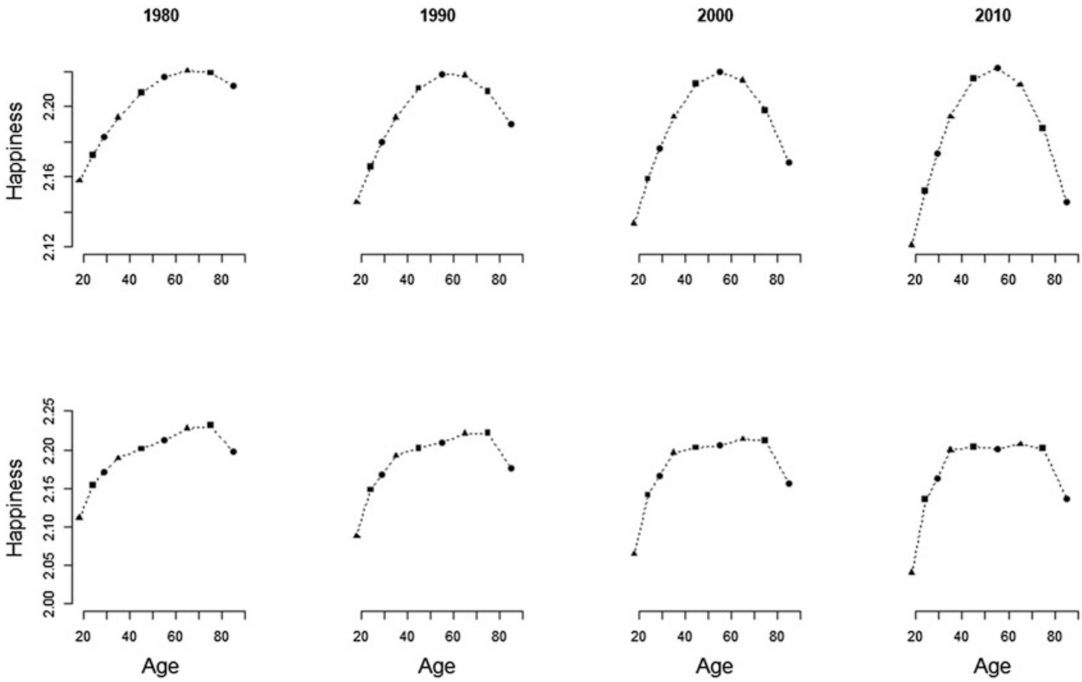
Age-Period-Cohort Models, Fig. 3 Cohort pattern in happiness: Cross-classified random-effects model

Specifically, happiness was regressed on age and age^2 in each of the 30 GSS waves, respectively. Coefficients from these models were used to estimate age-specific predicted happiness scores at each wave (1972–2014). Since happiness levels are known to fluctuate across time, linear regression lines were fit to each series of age-specific predicted happiness scores to adjust for period effects. Finally, to show the age trend in happiness, coefficients from these models were used to estimate age-specific predicted happiness scores in 4 years of the GSS (i.e., 1980, 1990, 2000, and 2010). Simply put, age effects were captured by controlling for age and age^2, period effects were adjusted for by smoothing results across time, and cohort effects were accounted for by excluding Boomers from the sample.

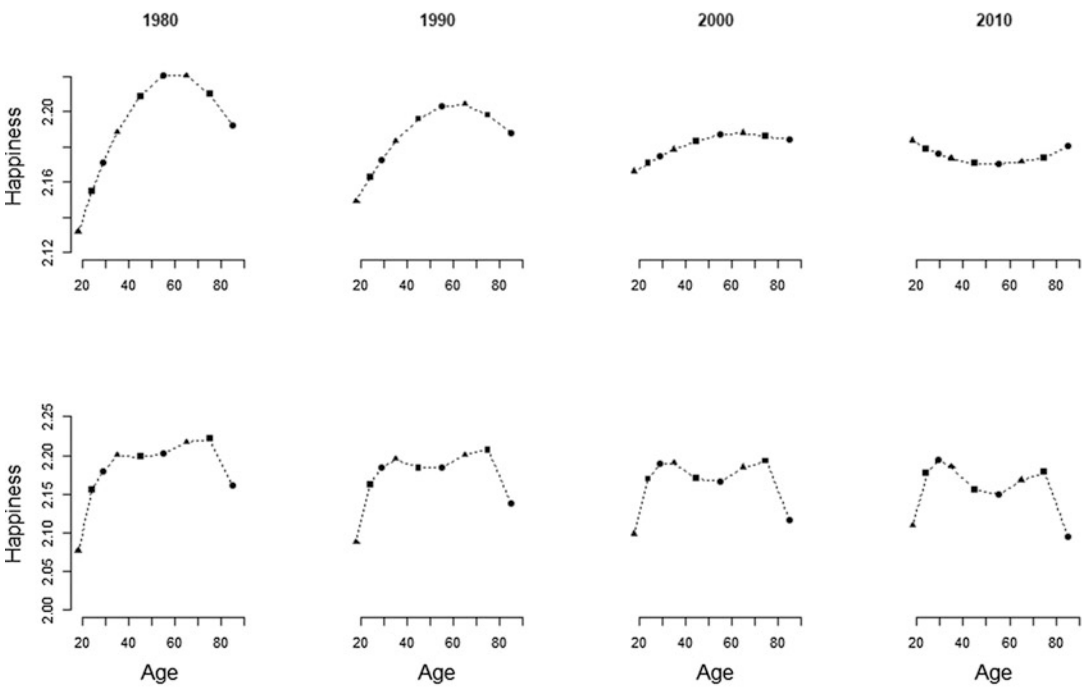
Results show that the age pattern in happiness has remained fairly constant over time, with the exception of the youngest and oldest age groups possibly becoming less happy in recent decades (see the top row in Fig. 4). However, this growing unhappiness among younger and older age groups may simply be because large age groups are missing in these analyses due to excluding the Boomers. To address this issue, a fourth-order polynomial age term (i.e., age^4) was used to better capture potential nonlinear age effects. The bottom row in Fig. 4 shows that the trend in the age-happiness pattern is indeed relatively constant, and only the youngest age group is shown to have become less happy over time – and *not* adults around age 30, as suggested by some scholars (e.g., Twenge et al. 2016).

Without prior APC knowledge, this approach would not be justifiable. To illustrate this point, the previous model was replicated, but with the Boomers included in the analytic sample. Results (see the top row in Fig. 5) show an opposite age pattern compared to the one obtained from the sample where the Boomers were excluded (see the top row of Fig. 4). Furthermore, the "trough"-like pattern shown in the bottom row of Fig. 5, which was computed using a fourth-order polynomial age term, clearly depicts the Boomers aging across time. In sum, this applied example highlights why methods based on minimal assumptions and estimable functions, such as the cross-classified random-effects model, are often considered ideal for APC analysis when prior APC knowledge is limited.

It is important to note that a second-order polynomial age term was used in the present analysis of the full analytic sample to examine the age pattern in happiness based on previous understandings of happiness across the life course among American adults (see Yang 2008). However, a fourth-order polynomial age term was used to examine the sample that excluded Boomers as an exercise to show the implications of removing a specific cohort from these analyses. The use of polynomial terms to identify nonlinear age patterns should be informed by theory, their use should fit the data.



Age-Period-Cohort Models, Fig. 4 Trend in the age pattern in happiness: Dummy variable model with Boomers excluded from the sample. Note: The top row depicts results from models that used a quadratic age term; the bottom row depicts results from models that used a fourth-order polynomial age term



Age-Period-Cohort Models, Fig. 5 Trend in the age pattern in happiness: Dummy variable model with Boomers included in the sample. Note: The top row depicts results from models that used a quadratic age term; the bottom row depicts results from models that used a fourth-order polynomial age term

Future Directions for Research

Aging scholars will find APC techniques to be increasingly fruitful as data sources continue to include more (and new) birth cohorts and time periods (see Fu et al. 2020). Initial research should focus on identifying the main effects of age, period, and cohort. Findings from these studies will likely lead to the modification of existing theories or even new theory development. Next, researchers may find it beneficial to examine interactions between individual- and/or structural-level variables and the three dimensions. Also, researchers should consider whether age and cohort patterns have changed over time (similar to the applied example in this entry).

Summary

Any scholar concerned with identifying age, period, and/or cohort effects should be aware of the APC identification problem and various methods to address it. This entry largely focused on techniques that can be used to examine repeated cross-sectional data. However, other APC approaches have been designed to examine different types of data (e.g., longitudinal panel data). This entry reflects a good starting point from which any aging scholar can begin a journey toward using APC techniques in her/his own research.

Cross-References

▶ Cross-sectional and Longitudinal Studies
▶ Hierarchical Model
▶ Life Course Perspective
▶ Repeated Cross-sectional Design

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