A New Age-Period-Cohort Method for Describing and Investigating Inter- and Intra-Cohort Effects*

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Abstract

Social scientists have frequently attempted to decompose temporal trends in various outcomes into three aspects of time processes: age, period, and cohort. The analytical problem that has faced researchers for decades is that these three distinct processes are linearly related to each other (cohort = period - age), so disaggregation of temporal trends has to rely on statistical assumptions that are difficult to verify. In this paper, we develop and introduce a new method, called the age-period-cohort-interaction (APC-I) model, for analyzing age, period, and cohort effects. Compared with other age-period-cohort methods, the APC-I model has two advantages: First, it does not rely on problematic statistical assumptions. Second, while other methods assume that cohort effects are constant from birth to death, the new APC-I model relaxes this assumption and allows researchers to test hypotheses about changes within cohorts. The APC-I method can provide fresh perspectives about how time and social events interact with social institutions such as family and schools to produce social inequality and affect population processes. Using 1974 to 2012 data from the General Social Survey, we demonstrate how this new model can be used to investigate inter- and intra-cohort variation in Americans' political views.

Introduction

Social scientists are often concerned with how demographic, social, economic, and health outcomes vary across time. For example, have death rates in the U.S. declined across birth cohorts? Have Americans become politically more liberal or conservative in recent decades? Do Americans' vocabularies decrease as they become older and has this changed over the past decades? Answering questions like these immediately requires analysts to consider simultaneously the roles of three distinct dimensions of time: *age* (how old people are at the time of interview), *period* (the year in which they are interviewed), and *cohort* (in these examples, the year in which they were born).

To separate the independent effects of age, period, and cohort, Mason et al. (1973) proposed an age-period-cohort (APC) accounting model. Unfortunately, this APC model suffers from an identification problem: the value for one of the three variables is completely determined by the other two: cohort = period – age. That is, researchers have sought to understand three dimensions of time, yet one dimension is an exact function of the other two dimensions. As a result, the APC model is not estimable. Various techniques have been developed to circumvent this identification problem, but they either omit one of the three dimensions (often period) or rely on statistical assumptions that are difficult or impossible to verify (Glenn 2005; Luo 2013a; Luo and Hodges 2013; O'Brien 2011; Rodgers 1982). We propose an alternative approach by developing an APC model that is tied more closely to concepts about what cohort represents and that does not rely on problematic statistical assumptions to distinguish age, period, and cohort effects.

This research has two primary objectives. First, drawing on the literature of sociology, demography, and biostatistics, we develop and introduce an innovative age-period-cohort model, called the age-period-cohort-interaction (APC-I) model, that can be used to investigate inter- and intra-cohort changes for both aggregated and individual-level data. The specification of this new APC-I model is informed by demographic and sociological theories, and the model bypasses the identification problem. As a result, valid estimates of age, period, and cohort patterns in social, demographic, and health outcomes can be obtained and assessed.

Second, using 1974 to 2012 data from the General Social Survey, we demonstrate how this new APC-I model can be used to describe age, period, and cohort trends in Americans' changing political landscape and to test "cumulative advantage" theory about intra-cohort changes and associated social conditions. The traditional APC accounting model assumes that cohort effects are established at birth and do not change over the life course, so even if it were not problematic on technical grounds, it could not be used to examine the "cumulative disadvantages" theory, in which the outcome of interest such as political outlook, death rates, and happiness, is heterogeneous *within* cohorts (Dannefer 2003, 1987; Hobcraft 1992). The APC-I model, in contrast, is less restrictive and flexible enough to test this important life course theory.

This paper proceeds as follows. We begin by comparing the concept of cohort effects that concerns demographers and sociologists and the type of cohort effects that are estimated in the classic APC accounting model. The disparities between the two reveal the theoretical nature of the identification problem in APC analysis. Next, we introduce the new APC-I model, provide theoretical and methodological rationales for it, describe how it is specified, and explain how inter- and intra-cohort effects can be estimated and tested. We then use an empirical example of political views to demonstrate how the APC-I model can be used to investigate inter- and intra-cohort dynamics. We conclude by discussing limitations of this new model.

Cohort Theories and the APC Accounting Model: Disparities between conceptual definition and operationalization

Cohort Analysis and Age-Period-Cohort Framework

Many researchers are interested in how demographic, social, economic, and health outcomes vary across time in a society in which individual biographies are shaped by social characteristics such as gender, education, and socioeconomic status. For example, demographers are interested in identifying factors that are responsible for the mortality decline in the 20^{th} century (Masters 2012). For another example, sociologists of religion have attempted to test the theory of secularization, a thesis that refers to the decline of religion in modern societies (Chaves 1989; Firebaugh and Harley 1991). Until 1970s, research on temporal processes had been dominated by an age-period paradigm, a paradigm that only considers shifts across age groups and time periods. *Age* is arguably one of the most important factors in social science research: a wide range of research has documented that many social, demographic, economic, and health outcomes change as one gets older (Cole 1971; Elder 1975; Lynch 2004; Borella et al. 2011). At the same time, social and historical changes, captured as a package by *period effects*, can affect individual outcomes including political views, vocabulary knowledge, and health conditions (Peng 1987; Smith 1990; Wilson and Gove 1999).

Demographers and sociologists have challenged this age-period paradigm, arguing that this type of research ignores an important dimension of temporal processes: *cohort*. A cohort refers to as a group of individuals who experience a significant event like birth, marriage, or graduation at the same age in their life course. Cohort is a key concept and useful analytical tool because cohort patterns reflect the formative effects of exposure to social events in one’s early childhood that act persistently over time (Ryder 1965). Social science literature has demonstrated the importance of cohort; omitting cohort in analyzing temporal trends may lead to spurious conclusions about age and period patterns. Therefore, answering questions about temporal processes of demographic, social, economic, and health outcomes requires analysts to simultaneously consider the distinct effects of age, period, and cohort.

To separate the independent age, period, and cohort effects, Mason et al. (1973) specified an analysis of variance (ANOVA) model, termed age-period-cohort (APC) accounting model[1]:

$$g(E(Y_{ij})) = \mu + \alpha_i + \beta_j + \gamma_k, \tag{1}$$

for age groups $i = 1,2, \dots, a$, periods $j = 1,2, \dots, p$, and cohorts $k = 1,2, \dots, (a + p - 1)$, where $\sum_{i=1}^{a} \alpha_i = \sum_{j=1}^{p} \beta_j = \sum_{k=1}^{a+p-1} \gamma_k = 0$. $E(Y_{ij})$ denotes the expected value of the outcome of interest Y for the ith age group in the jth period of time; g is the "link function"; α_i denotes the mean difference from the global mean μ associated with the ith age category; β_j denotes the mean difference from μ associated with the jth period; γ_k denotes the mean difference from μ due to the membership in the kth cohort. The usual ANOVA constraint applies where the sum of coefficients for each effect is set to zero. Unfortunately, without additional information, this APC model cannot estimate the independent effects of age, period, and cohort. The next two subsections discuss methodological and theoretical limitations of the APC accounting model.

Methodological Critique: What the APC accounting model estimates

The methodological problem in the APC accounting model can be illustrated more explicitly using a generic form for the statistical model. Suppose that the outcome of interest is normally distributed, then model (1) can be written as follows:

[1] This is called an "accounting" model because it is not intended for causal analysis.

$$Y = Xb + \varepsilon, \tag{2}$$

where Y is a vector of outcomes; X is the design matrix implied by model (1); b denotes a parameter vector whose elements correspond to the effects of age, period, and cohort groups; and ε denotes random errors with distribution centered on zero. Because of the linear dependency between age, period, and cohort, the design matrix X has rank one less than full, so an infinite number of solutions fit data equally well. That is, the data cannot distinguish different estimation results, so a constraint must be imposed in order to choose one set of estimates.

Scholars have emphasized that the choice of the constraint must be based on theoretical ground or external information (Fienberg 2013; Glenn 2005; Luo 2013b; O'Brien 2013), but such theoretical information often does not exist. More importantly, even when a constraint imposed on the model (1) can be justified by theoretical accounts, the meanings of the estimated "cohort effects" obtained from the APC accounting model (1) can be difficult to understand. To illustrate, suppose that each of the age, period, and cohort effect has linear and quadratic trends, then model (1) can be written as

$$Y = \beta_0 + \beta_1 a + \beta_2 a^2 + \beta_3 p + \beta_4 p^2 + \beta_5 c + \beta_6 c^2 + \varepsilon, \tag{3}$$

where Y is the outcome, β_0 denotes the grand mean, and $\beta_1, \beta_2, \ldots, \beta_6$ denotes the coefficients for linear and quadratic age, period, and cohort terms, respectively. Because $cohort = period - age$, replacing cohort terms with age and period results in

$$Y = \beta_0 + \beta_1 a + \beta_2 a^2 + \beta_3 p + \beta_4 p^2 + \beta_5 (p - a) + \beta_6 (p - a)^2 + \varepsilon. \tag{4}$$

Simple algebra then gives

$$Y_{ij} = \beta_0 + \beta_1 a + \beta_2 a^2 + \beta_3 p + \beta_4 p^2 + \beta_5 (p - a) + \beta_6 (a^2 + p^2 - 2 \cdot a \cdot p)^2 + \varepsilon_{ij}. \tag{5}$$

Eq. (5) shows that the "cohort effects" that APC model (1) attempts to estimate in fact involve linear age and period effects, quadratic age and period effects, and most crucially an age-by-period interaction. The use of a continuous term to index cohort membership may seem odd to APC analysts, but we use this strategy only to demonstrate the implication of the linear dependency among age, period, and cohort for estimating and interpreting cohort effects in the classic APC accounting model. Eq. (5) is revealing because it shows that even when researchers can choose a set of estimates (i.e., a constraint on β) based on theoretical accounts, the resulting estimates for cohort effects are a combination of linear and nonlinear age and period effects and their interaction. This is unfortunate because the APC accounting model is designed to isolate the "simultaneously independent" effects of age, period, and cohort, but apparently it has not achieved this goal.

The APC literature has emphasized the "unusual" methodological challenge of separating the effects of age, period, and cohorts (Fienberg and Mason 1985; Holford 1983, 2006; Kupper et al. 1983, 1985), but inadequate attention has been given to the theoretical problem that gives rise to the methodological problem in the APC accounting model. In the following subsection, we argue that the APC accounting model fails not so much because of the identification problem, but because it incorrectly assumes that there *are* independent, additive age, period, and cohort effects in the phenomena of interest.

Theoretical Critique: How cohort effects are defined

In his seminal work, Norman Ryder (1965) offered a theoretical vision about how cohort effects manifest:

> "The aggregate by which the society counterbalances attrition is the birth cohort, those persons born in the same time interval and aging together. Each new cohort makes fresh contact with the contemporary social heritage and carries the impress

> of the encounter through life. … The new cohorts provide the opportunity for social change to occur. They do not cause change; they permit it. If change does occur, it differentiates cohorts from one another, and the comparison of their careers becomes a way to study change. The minimal basis for expecting interdependency between intercohort differentiation and social change is that change has variant import for persons of unlike age, and that the consequences of change persist in the subsequent behavior of these individuals and thus of their cohorts."(1965: 844)

He further elaborated three basic notions on which cohort analysis rest:

> "persons of age *a* in time t are those who were age *a*-1 in time t-1; transformations of the social world modify people of different ages in different ways; the effects of these transformations are persistent. In this way a cohort meaning is implanted in the age-time specification." (1965: 861)

According to this conceptualization, a cohort effect is *defined* as the interaction between age and period effects: A social or historical transformation that has uniform consequences for people of all ages can thus have no cohort effect; likewise, an age-related process that works the same way for all time periods also cannot have a cohort effect. Conceptually, this is different from thinking about cohort as having independent effects net of period and age effects. While prior work in this area (at least implicitly) sough to isolate the independent effect of cohort among people who are equivalent with respect to age and period, in the new APC model that we introduce below, we conceptualize cohort as the degree to which age and period effects are moderated by one another.

What does this alternate notion of cohorts mean for describing and explaining temporal trends in demographic, social, economic, and health outcomes? Instead of assuming that period effects do not exist or that there are independent effects of cohort net of age and period effects, we argue that research should begin by explicitly describing the degree to which age effects vary across time periods and or equivalently, the extent to which period effects vary across age groups. Then, if the effects of period are the same across age groups and or equivalently, if the effects of age are the same across periods, we must identify explanations for trends in the outcome of interest that do not rely on cohort processes, i.e., that are consistent with this empirical pattern. On the other hand, if there are such moderating effects, then we must seek explanations that are consistent with this empirical pattern. It seems very likely, for example, that the temporal changes in church attendance have occurred differently in different age groups; older people's church-going activity is probably less amenable to change, and the church attendance of younger people has been declining. Thus church attendance is a cohort characteristic and might explain cohort trends in Americans' political views—but only if the effects of period vary by age and or vice versa.

Inter-Cohort Differences and Intra-Cohort Dynamics

As argued by Hobcraft et al. (1982), another theoretical limitation of classic APC analyses is that they assume that cohort effects are constant across the life course. That is, the classic analysis not only assumes that there is an independent effect of cohort net of age and period, but also that this effect of cohort does not change for individuals from birth to death. Under the conceptualization of cohort described above, this assumption can be relaxed. For example, being a young adult when the civil rights movement was sweeping through America may matter for political views, but it is not necessary to assume that those effects persist into later life for that birth cohort. This reconceptualization of cohort allows us to test various theoretical ideas including the "cumulative advantage" hypothesis (Dannefer 1987, 2003; DiPrete and Eirich 2006). In its general form, the "cumulative advantage" hypothesis concerns the degree to which advantages or disadvantages persist or change with age. If this hypothesis is correct, we should see particular patterns of interactions between age and period such that members of specific birth cohorts are persistently or increasingly distinctive with respect to political views as they age.

Unfortunately, beyond the serious technical limitations described above, current APC models like the intrinsic estimator (Yang et al. 2008) and cross-classified APC models (Yang and Land 2006, 2008) are not useful for understanding cohort effects because they conceive of cohorts in a way that departs from the concept as described by Ryder (1965) and because they assume that cohort effects are constant across the life course.

Towards Paradigm Shift: A new model

The preceding discussion of the methodological limitations of the APC accounting model and associated estimation techniques is not to deny the theoretical importance or explanatory power of the concept of a "cohort." The point, rather, is that any search for an "ultimate" statistical solution under the APC accounting framework attempting to estimate cohort effects independent of age and period effects is a "futile" (Glenn 1976) and "unholy" (Fienberg 2013) quest. To solve these problems, researchers must move beyond the accounting framework and precipitate a paradigm shift (Kuhn 1996).

One direction that we propose is to observe that each of the hypotheses about cohort effects, namely "constant effects", "accumulative advantages," and "compensation hypothesis" corresponds to specific constraints on the age-by-period interaction or a specific form of that interaction, which is an alternative to focusing on nonlinear cohort effects as suggested by Holford (1992) and Fienberg (2013). This new APC model is closely tied to theoretical ideas about cohort effects, bypasses the identification problem, and is flexible enough to test various hypotheses about changes within cohorts, and thus may be a step towards a paradigm shift in APC research. We first describe below how the new model is specified and suggest estimation and testing techniques for it. We then demonstrate how the new model can be used to test theoretical ideas about inter- and intra-cohort changes using the example of political views.

Model Specification, Estimation, and Testing

The APC accounting model (1), in which cohort effects are considered independent of and additive to age and period effects, implies that cohort effects can occur when the effects of period apply equivalently to all age groups. However, as we discuss above, sociological and demographic theories suggest that cohort effects cannot be observed when period effects do not differ across age groups. Informed by this theoretical insight, we develop a new model, called the age-period-cohort-interaction (APC-I) model, that explicitly considers cohort as a specific form of the age-by-period interactions. The general form of this model can be written as

$$g(E(Y_{ij})) = \mu + \alpha_i + \beta_j + \alpha\beta_k, \tag{6}$$

where g, Y_{ij}, μ, α_i and β_j are defined as in model (1). Model (6) differs from model (1) in how cohort effects are modeled; here, cohort effects are considered as a specific form of (we'll come back to this point in the next paragraph) the age-by-period interaction. In statistics, the interaction between two variables describes the differential effects of one variable depending on the level of the other variable (Scheffé 1959). In the context of APC research, if the temporal patterns of the outcome of interest can be attributed to cohorts, significant age-by-period interactions should be detected. When cohort membership does not affect the outcome—that is, when the effects of historical or social shifts (period effects) are no different across age categories—then age-by-period interactions should not be observed.

However, not all age-by-period interactions correspond to cohort effects as defined by sociological and demographic theories. Rather, only the set of age-by-period interactions that definine specific patterns in the diagonal cells of an age-by-period cross-classification can be considered to represent effects due to cohort membership. Therefore, we measure the demographic and sociological sense of cohort effects as a specific form of the age-by-period interactions. To illustrate what "a specific form of the age-by-period interactions" means, compare the APC-I model (6) with model (7), an ANOVA model with age, period, and their interactions:

$$g(E(Y_{ij})) = \mu + \alpha_i + \beta_j + \alpha\beta_{ij}. \tag{7}$$

Suppose that for a set of normally-distributed data with five age categories and five periods, model (7) yields $(5-1)\cdot(5-1) = 16$ independently-varying estimates for the $5 \cdot 5 = 25$ age-by-period categories, where the remaining $25 - 16 = 9$ quantities can be computed using the usual ANOVA constraint. In the top panel of Table 1, the expected value of the outcome $E(Y_{ij})$ in each cell is represented in terms of the unknown parameters α_i, β_j and $\alpha\beta_k$ in model (6). In the bottom panel of Table 1, the expected value in each cell is represented in terms of the unknown parameters α_i, β_j and $\alpha\beta_{ij}$ in model (7).

[Table 1 About Here]

Consider, for example, the 5th cohort in the diagonal that runs from the upper-left to the lower-right. The effects of belonging to that cohort, $\alpha\beta_5$, in the top panel of Table 1 correspond to five elements in the age-by-period interactions, $\alpha\beta_{11}, \alpha\beta_{22}, \alpha\beta_{33}, \alpha\beta_{44}$, and $\alpha\beta_{55}$, in the bottom panel. Note that these five age-by-period interactions are unrestricted in model (7), meaning that they can take on any values (subject to summing to zero down columns and across rows). In model (6), these five age-by-period interactions are replaced with a single parameter $\alpha\beta_5$, conforming to a particular theory about changes over the life course within a cohort.

Accordingly, in the APC-I model, the variation between cohorts may be examined by testing the difference between the groups of age-by-period interactions that lie along the $(A + P - 1)$ diagonals of the age-by-period cross-classification. The variation within cohorts can be investigated by imposing a restriction on the group of age-by-period interactions that correspond to a cohort of interest, so testing the hypothesis about $\alpha\beta_5$ is equivalent to testing a specific pattern in $\alpha\beta_{11}, \alpha\beta_{22}, \alpha\beta_{33}, \alpha\beta_{44}$, and $\alpha\beta_{55}$. We describe a three-step procedure below to estimate and test inter-cohort differences. We also suggest a technique for testing three theories about intra-cohort effects, namely "constant effects", "accumulative advantages", and "compensation hypothesis". The modeling and testing procedures described in Step 1 below can be carried straightforward. We will provide exemplary R code for the tests described in Steps 2 and 3 in the Appendix.

Step 1. A *global* F test: Are there variations in the outcome of interest associated with cohort membership? First, run model (7) that includes main age effects, main period effects, and their interactions. Then examine the variation attributable to the age-by-period interactions with $(a-1) \times (p-1)$ degree of freedom. An F statistic at desirable significance level, say 0.05 indicates that cohort effects may be operative. While such a global F test does not characterize cohort effects, with a non-significant *F* test result one may conclude that cohort membership does not affect the outcome that one is interested in and no need to do tests described in Step 2 or Step 3 that concern cohort patterns.

Step 2. *Local* (cohort-specific) *F* tests: Does the membership of a given cohort matter? We create an *F* test technique to address this question by testing a hypothesis about each set of the age-by-period interactions that corresponds to a given cohort. This local *F* test examines taken together, whether that group of age-by-period interactions explains a significant proportion of variation in the outcome. If the local *F* test rejects the null hypothesis, then one may conclude that the membership of that cohort has effects on the outcome of interest. However, these *F* tests does not allow researchers to distinguish which cohort differs from others in the outcome of interest, so we develop two *t* tests for understanding between-cohort differences and within-cohort dynamics.

Step 3.1. *t* tests for inter-cohort variation. For each of those cohorts whose membership has an effect on the outcome based on the local *F* test, compute the average of the age-by-period interactions representing that cohort and use a *t* test that we develop to examine whether that cohort, on average, has an effect on the outcome of interest. Then use these averages and associated *t* test results to assess patterns across cohorts in the outcome of interest.

Step 3.2 *t* tests for intra-cohort variation. For cohorts that contribute to the variation in the outcome according to the local *F* test, conduct a *t* test of a set of linear (and quadratic if desirable) orthogonal polynomial contrasts that we create to investigate whether the advantages or disadvantages of members of a given cohort cumulate, remain stable, or disappear in their life course. Table 2 provides a guideline about how to use the *F* and *t* tests results to test the three theoretical ideas about changes within cohort, namely “constant effects”, “accumulative advantages", and "compensation hypothesis". Specifically, it can be considered supporting evidence for the cumulative advantage/disadvantage hypothesis when the average or mean effects and linear slope for a given cohort have the same sign, as shown in the upper-left and lower-right cells in Table 2. When the average and linear slope have opposite signs, as in the situations shown in the upper-right and lower-left cells in Table 2, a counter-argument of cumulative advantage/disadvantage appears to be true: a cohort's initial advantage/disadvantage is disappearing as that cohort ages. When the mean effect of a cohort is not statistically significant but the linear slope is significant, it provides evidence favoring compensation theory. If the linear slope is not significant but the mean effect is significant, then the constant effects argument seems plausible. If neither the average nor the slope is significant, it means that there is no clear pattern of cohort variation, and the significant local *F* test is likely a result of some sort of deviation that does not conform to any theoretical idea of cohort effects.

[Table 2 About Here]

Two remarks about the three-step procedure: First, the idea of using model statistics in APC analysis to select the "best-fitting" model is not news. For example, Clayton and Schifflers (1987) recommended using deviance or likelihood-ratio criterion to choose among a model that includes only age, an age-period model, an age-cohort model, or an age-period-cohort model. For another example, Yang (2008) also suggested comparing these models and viewed model fit statistics as a justification for using a constrained approach like the intrinsic estimator. However, the purpose of the global *F* test proposed here is neither model selection nor verifying technical constraints on the unknown age, period, and cohort parameters; because we consider cohort effects as age-by-period interactions, the global *F* test serves as an explicit measure and necessary condition for cohort effects.

Second, we caution that researchers should be careful about interpreting cohort effects when less than three age-by-period interactions lie along the cohort diagonal because it may be potentially misleading to treat the slope determined by very limited data (e.g., two age-by-period cells), usually for the youngest or the oldest cohorts, as a general trend for that cohort in their life course. The more age-by-period cells we observe for a cohort, the more accurate the estimates are for understanding changes within that cohort.

Are Americans Becoming More Liberal or Conservative: An empirical example

In this section, we demonstrate how the new APC-I model and testing strategies described above can be used to examine inter- and intra-cohort changes in Americans' political views. Because liberalism/conservativism is a complex concept to describe and measure, we do not attempt to make any conclusive assessment about temporal trends in America's political landscape using a single indicator; rather, the main objective of this section is to demonstrate how the APC-I model can be used to investigate age, period, and cohort trends in a sociologically interesting phenomenon.

Sociologists have long been interested in how Americans' political views have changed over time, but there is no consensus about the sources of the temporal trends. For example, "the general liberal hypothesis" proposed by Smith (1982, 1990) posits that America has been moved in a liberal direction by modernization and liberal idealism. In contrast, Ellis and Stimson (2012) showed that Americans who labeled themselves as conservative outnumber those called themselves liberals. We apply the APC-I model to the General Social Survey (GSS) data to examine the three dimensions of time, namely age, period, and cohort, in America's political outlook. Almost every year from 1974 to 1994 and then every other year from 1996 to 2012—26 different years in total, the GSS asks respondents to place themselves on a seven-point liberal/conservative scale (POLVIEWS: 1—extremely liberal; 2—liberal; 3—slightly liberal; 4—moderate; 5—slightly conservative; 6—conservative; 7—extremely conservative). Age and year of interview are ascertained in every survey. We select respondents who participated in the 1974 through 2012 GSS surveys in years in which this question is administered. We exclude respondents with missing data on POLVIEWS, age, or survey year, resulting a sample of 47,729 people. We constructed 15 age groups (18-19, 20-24, 25-29, … 80-84, and 85-89), nine periods (1974, 1975-1979, 1980-1984, …, 2005-2009, and 2010-2012), and thus 23 birth cohorts (1885, 1890, …, 1990, 1993)[2]. Table 3 presents the descriptive statistics for the outcome variable (POLVIEWS) and for the three time-related predictors (age, period, and cohort). In this exercise, we attempt to answer three questions about the temporal trends in political views: (1) Do American's political views vary as a function of age, period, and cohort membership? (2) Which cohorts are more conservative or liberal than other cohorts? (3) Are the cohort effects on political views constant, accumulating, or disappearing over the life course?

[Table 3 About Here]

[2] In a table of five-year age groups and five-year periods, birth cohorts are defined by diagonals and extend over a nine-year interval. For example, the observations in the years 1975 through 1979 for people in the 30 to 34 age group correspond to the birth cohort of 1941 to 1949. Conventionally, each cohort is identified by its mid or central birth year (see, e.g., Mason and Winsborough 1973; O'Brien 2011; Yang and Land 2008). We follow this practice and so, for example, the 1945 cohort refers to the group of people born between 1941 and 1949. It is worth noting that birth cohorts overlap with adjacent cohorts when so defined. This overlap is usually ignored in statistical modeling (Kupper et al. 1985).

Tables 4 and 5 reports—Figure 1 illustrates—estimated age, period, inter- and intra-cohort trends in POLVIEWS. Models 1 and 2 in Table 4 describe bivariate relationships between POLVIEWS and age and period, respectively. Model 3 considers the ways in which political views vary by age and period under the assumption of no cohort effects. Model 4 then describes variation in POLVIEWS as a function of age, period, and cohort, i.e., the age-by-period interactions simultaneously. An inspection of the estimated age and periods effects in Model 1 through Model 4 shows that age trends in political views do not differ in a cross-over or qualitative manner depending on periods, so a meaningful description of a general age trend and a general period trend is warranted. Moreover, model fit statistics—including a global *F* test ($F = 2.178$, df = 112, $p < 0.001$), AIC, and adjusted R-squared—suggest that the model that includes the age-by-period interactions (Model 4) fits better than the model without them (Model 3); note that the interactions corresponding to cohort effects in Model 4 are reported in Table 5. We thus conclude that cohort membership is likely to affect political views, where cohort effects are conceptualized and modeled as described above.

[Table 4 About Here]

[Table 5 About Here]

As in *prior* research, we find that conservatism increases with age monotonically. The estimated period effects in the models in Table 4 suggest that the America was especially liberal in early 1970s was especially conservative in the 1980s and 1990s. In general, the magnitude of the period effects is smaller than those that of the age effects. These findings also suggest that the effects of age do vary across periods, at least in some cases; likewise, the effects of period are not always the same for people in all age groups. Consequently, explanations of these trends should focus on at least some historical factors that might have mattered differently across age groups.

Table 5 presents the remainder of the results from Model 4 in Table 4: the estimated age-by-period interactions, rearranged so that each column corresponds to birth cohorts (as represented by the age-by-period interactions that lie along the diagonal cells in the age-by-period cross-classifications). Local (cohort specific) *F* tests about these multiple age-by-period interactions indicate, generally speaking, whether belonging to particular cohorts is associated with political views. The results show that membership of the 1890, 1935, 1945, 1950, 1955, 1965, and 1975 cohorts plays a role in political outlook. The between-cohort *t* tests in Table 5 suggest that on average, early baby boomers, the 1945 and 1950 cohorts, are especially liberal whereas the 1965 cohort is especially conservative. We also find that supporting evidence for the "constant effects hypothesis" for the intra-cohort variation in political views: The intra-cohort *t* tests indicate that there is little variability across ages and periods within cohorts, although people of all cohorts tend to become more and more conservative as they age and their political views are subject to social and historical influences.

Discussions and Conclusion

Despite the conceptual merits and explanatory power of age, period, and cohort, traditional age-period-cohort (APC) models that are designed to separate the independent effects of the three dimensions of time suffer from an identification problem. As a result, no reliable estimates of age, period, or cohort effects can be ascertained. While this identification problem has been considered a methodological challenge, we argue that the identification problem is theoretical in nature: The cohort effects conceptualized in demographic and theoretical literature and those estimated in traditional APC models are not the same, which gives rise to the technical problem. In this paper, we develop a new APC model—the APC-I model—that is more closely tied to the conceptual ideas of cohort effects, in which cohort effects are quantified as a specific form of the age-by-period interaction. This model has two advantages. First, like any two-way ANOVA model with interactions, this model is identifiable and does not incur the identification problem. Second, in addition to the estimation problem, traditional APC models implicitly assume that the cohort effects are constant through the life course. Under the APC-I model, this assumption can be relaxed, so researchers can investigate the life course dynamics within cohorts. Using the General Social Survey data, we have demonstrated how this model can be used to understand the age, period, inter-, and intra-cohort variation in political views.

The view that cohort effects can be quantified as age-by-period interactions has not gone unnoticed in the APC literature. For example, Holford (1983) noted that "[a] model which assumes that…there is an additive effect due to age, period and cohort is in itself arbitrary. We might instead have considered interactions, but in fact if we look at interactions among any two factors, the third factor spans a subspace of that interaction space." (p. 322) While we agree with Holford that technically it is true that the effects of the third variable can be expressed by the interaction between the other two variables, the APC-I model in which cohort effects are explicitly measured as a specific form of age-by-period interaction is developed based on the theoretical ground of how cohort effects are conceptualized in relation to age and period effects. In their insightful article, Fienberg and Mason (1985) encouraged researchers to "begin with conceptualization and attempt to move toward explicit measurement, in order to test understanding of the interaction." (p. 83) To the extent that the APC-I model is explicitly tied to the conceptualization of cohort effects in sociological and demographic literatures, we believe that the APC-I model is promising in advancing APC research.

Although the APC-I model is designed for the APC analysis, the conceptual critiques and methodological ideas can be extended to many other fields in which focal explanatory variables are exactly related. For example, scholars of status inconsistency study the likelihood of a person attaining higher or lower socioeconomic status than their parents and the consequences of changes in status for various outcomes including happiness, marriage, and health conditions. Researchers of assortative mating are interested in how marriage forms between persons of the same or different levels of educational attainment, and the implications of such educational homogeneity or heterogeneity for marriage duration, life satisfaction, and other economic and health well-beings. Despite long-standing interest in these areas among sociologists and demographers, these lines of scholarship suffer from a methodological problem that is the same in nature as in APC analysis: the third variable is completely determined by the other two. Specifically, in status inconsistency studies, status inconsistency equals adult socioeconomic status minus status of their parents; in educational homogamy research, educational difference equals husband's education minus wife's education. Several methods have been developed to address this estimation problem, but none of them are satisfactory from a statistical point of view (Hope 1975; Houle 2011; Sobel 1981). Although the APC-I model that we develop in this paper is designed to understand age, period, and cohort effects, it can potentially be modified to address these important sociological issues. We encourage future research on these topics.

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Tables and Figures

Table 1. Unobserved Parameters in Models (6) and (7)

			Period				
			1	**2**	**3**	**4**	**5**
Parameters in Model (6)	**Age**	**1**	$\mu+\alpha_1+\beta_1+\alpha\beta_5$	$\mu+\alpha_1+\beta_2+\alpha\beta_6$	$\mu+\alpha_1+\beta_3+\alpha\beta_7$	$\mu+\alpha_1+\beta_4+\alpha\beta_8$	$\mu+\alpha_1+\beta_5+\alpha\beta_9$
		2	$\mu+\alpha_2+\beta_1+\alpha\beta_4$	$\mu+\alpha_2+\beta_2+\alpha\beta_5$	$\mu+\alpha_2+\beta_3+\alpha\beta_6$	$\mu+\alpha_2+\beta_4+\alpha\beta_7$	$\mu+\alpha_2+\beta_5+\alpha\beta_8$
		3	$\mu+\alpha_3+\beta_1+\alpha\beta_3$	$\mu+\alpha_3+\beta_2+\alpha\beta_4$	$\mu+\alpha_3+\beta_3+\alpha\beta_5$	$\mu+\alpha_3+\beta_4+\alpha\beta_6$	$\mu+\alpha_3+\beta_5+\alpha\beta_7$
		4	$\mu+\alpha_4+\beta_1+\alpha\beta_2$	$\mu+\alpha_4+\beta_2+\alpha\beta_3$	$\mu+\alpha_4+\beta_3+\alpha\beta_4$	$\mu+\alpha_4+\beta_4+\alpha\beta_5$	$\mu+\alpha_4+\beta_5+\alpha\beta_6$
		5	$\mu+\alpha_5+\beta_1+\alpha\beta_1$	$\mu+\alpha_5+\beta_2+\alpha\beta_2$	$\mu+\alpha_5+\beta_3+\alpha\beta_3$	$\mu+\alpha_5+\beta_4+\alpha\beta_4$	$\mu+\alpha_5+\beta_5+\alpha\beta_5$
Parameters in Model (7)	**Age**	**1**	$\mu+\alpha_1+\beta_1+\alpha\beta_{11}$	$\mu+\alpha_1+\beta_2+\alpha\beta_{12}$	$\mu+\alpha_1+\beta_3+\alpha\beta_{13}$	$\mu+\alpha_1+\beta_4+\alpha\beta_{14}$	$\mu+\alpha_1+\beta_5+\alpha\beta_{15}$
		2	$\mu+\alpha_2+\beta_1+\alpha\beta_{21}$	$\mu+\alpha_2+\beta_2+\alpha\beta_{22}$	$\mu+\alpha_2+\beta_3+\alpha\beta_{23}$	$\mu+\alpha_2+\beta_4+\alpha\beta_{24}$	$\mu+\alpha_2+\beta_5+\alpha\beta_{25}$
		3	$\mu+\alpha_3+\beta_1+\alpha\beta_{31}$	$\mu+\alpha_3+\beta_2+\alpha\beta_{32}$	$\mu+\alpha_3+\beta_3+\alpha\beta_{33}$	$\mu+\alpha_3+\beta_4+\alpha\beta_{34}$	$\mu+\alpha_3+\beta_5+\alpha\beta_{35}$
		4	$\mu+\alpha_4+\beta_1+\alpha\beta_{41}$	$\mu+\alpha_4+\beta_2+\alpha\beta_{42}$	$\mu+\alpha_4+\beta_3+\alpha\beta_{43}$	$\mu+\alpha_4+\beta_4+\alpha\beta_{44}$	$\mu+\alpha_4+\beta_5+\alpha\beta_{45}$
		5	$\mu+\alpha_5+\beta_1+\alpha\beta_{51}$	$\mu+\alpha_5+\beta_2+\alpha\beta_{52}$	$\mu+\alpha_5+\beta_3+\alpha\beta_{53}$	$\mu+\alpha_5+\beta_4+\alpha\beta_{54}$	$\mu+\alpha_5+\beta_5+\alpha\beta_{55}$

Table 2. Testing Intra-Cohort Changes

		Sign of the Linear Slope		
		+	0	-
Sign of the intercept	+	Cumulative Advantage	Constant Effects	Converging
	0	Compensation	No Clear Pattern	Compensation
	-	Converging	Constant Effects	Cumulative Disadvantage

Table 3. Descriptive Statistics for All Analytic Variables, General Social Survey, 1974-2012

Variable	Description	N	Mean	SD	Min	Max
Political views (POLVIEW)	1-Extremely Liberal; 7-Extremely Conservative	47729	4.105	(1.37)	1	7
Age(AGE)	Age at time of survey	47729	45.557	(17.39)	18	89
Period (YEAR)	Survey year	47729	-	-	1974	2012
Cohort	Birth year	47729	-	-	1885	1994

Note: Analysis includes GSS respondents who participated in the 1974 through 2012 GSS surveys in years in which POLVIEWS was administered and for whom POLVIEW and year of birth are available. Words in parentheses are GSS variable names.

Table 4. Estimated Age, Period, and Cohort Effects on Pollitical Views, General Social Survey, 1974-2012

		Model 1		Model 2		Model 3		Model 4	
Intercept		4.149	***	4.093	***	4.138	***	4.140	***
	18-19	-0.353	***	—		-0.347	***	-0.343	***
	20-24	-0.342	***	—		-0.340	***	-0.357	***
	25-29	-0.219	***	—		-0.218	***	-0.250	***
	30-34	-0.167	***	—		-0.169	***	-0.148	***
	35-39	-0.086	***	—		-0.090	***	-0.087	***
	40-44	-0.020		—		-0.024		0.006	
	45-49	-0.009		—		-0.012		0.001	
Age	50-54	0.045	*	—		0.047	*	0.056	*
	55-59	0.098	***	—		0.102	***	0.118	***
	60-64	0.099	***	—		0.102	***	0.094	***
	65-69	0.145	***	—		0.147	***	0.165	***
	70-74	0.172	***	—		0.171	***	0.149	***
	75-79	0.180	***	—		0.178	***	0.195	***
	80-84	0.188	***	—		0.185	***	0.107	*
	85-89	0.270	***	—		0.268	***	0.296	***
	1974	—		-0.112	***	-0.099	**	-0.115	*
	1975-79	—		-0.063	***	-0.048	**	-0.040	
	1980-84	—		0.026		0.041	*	0.056	*
	1985-89	—		-0.004		0.003		0.004	
Period	1990-94	—		0.055	***	0.053	***	0.066	***
	1995-99	—		0.052	**	0.054	**	0.058	*
	2000-04	—		0.043	*	0.036	*	0.017	
	2005-09	—		0.023		0.004		0.001	
	2010-12	—		-0.021		-0.045	*	-0.048	
Cohort		—		—		—		**(See Table 5)**	
Adujsted R^2		0.014		0.001		0.015		0.017	
AIC		164661		165280		164633		164613	
N		47729		47729		47729		47729	

Note: Analysis includes GSS respondents who participated in the 1974 through 2012 GSS surveys in years in which POLVIEWS was administered and for whom POLVIEWS and year of birth are available. Figures reresent Iteratively reweighted least squares regression coefficients coded to sum to zero. ***=p<0.001 ; ** = p < 0.01 ; * = p < 0.05

Table 5. Estimated Within- and Between-Cohort Trends in Political Views as Ascertained by Age-Period Interactions in Model 4 from Table 4, General Social Survey, 1974-2012

		Birth Cohort											
		1885	**1890**	**1895**	**1900**	**1905**	**1910**	**1915**	**1920**	**1925**	**1930**	**1935**	**1940**
Age	18-19												
	20-24												
	25-29												
	30-34												0.180
	35-39											-0.016	0.070
	40-44										0.223 *	0.098	-0.033
	45-49									0.117	0.159 *	0.019	-0.046
	50-54								0.082	0.096	0.070	0.013	0.024
	55-59							0.212	0.022	0.153	0.027	-0.182 **	-0.046
	60-64						-0.032	0.032	-0.020	0.032 *	0.043	0.070	0.085
	65-69					0.068	-0.041	-0.148	-0.142 *	-0.010	0.162 *	0.144	0.011
	70-74				-0.102	0.006	-0.044	-0.014	0.058	-0.021	0.011	0.214 **	-0.108
	75-79			0.163	0.046	0.011	-0.110	-0.006	-0.133	-0.052	0.031	0.051	
	80-84		-0.632 *	-0.037	0.146	0.174	0.080	-0.113	0.024	0.203 *	0.155		
	85-89	0.123	0.029	0.142	-0.080	0.158	0.028	-0.166	-0.247 *	-0.013			
	Step 2:												
Step 1:	Local F Test	na	4.376 *	0.563	0.727	0.964	0.605	1.521	1.729	1.505	1.913	2.521 **	0.927
Global F	**Step 3.1:**												
Test	Between	0.123	-0.301	0.089	0.003	0.083	-0.020	-0.029	-0.045	0.056	0.098	0.046	0.015
2.647 ***	**Step 3.2:**												
	Intra-Cohort	na	0.468	-0.015	0.037	0.110	0.071	-0.243	-0.188	-0.085	-0.082	0.119	-0.141

Note: Analysis includes GSS respondents who participated in the 1974 through 2012 GSS surveys in years in which POLVIEWS was administered and for whom POLVIEWS and year of birth are available. Figures resesent Iteratively reweighted least squares regression coefficients coded to sum to zero. Age and period coefficients are those presented in Table 4, Model 4. The global F test tests the hypothesis that taken together whether cohort effects exist. The local F test examines *which* cohort membership has an effect on political views. Between-cohort t tests look at the avarage effects of each cohort. Within-cohort tests investigate the linear trend in the life course of each cohort.
***=p<0.001 ; ** = p < 0.01 ; * = p < 0.05

Table 5. (Continued) Estimated Within- and Between-Cohort Trends in Political Views as Ascertained by Age-Period Interactions in Model 4 from Table 4, General Social Survey, 1974-2012

		Birth Cohort										
		1945	**1950**	**1955**	**1960**	**1965**	**1970**	**1975**	**1980**	**1985**	**1990**	**1994**
Age	18-19			0.018	-0.093	-0.090	0.102	-0.008	0.227	-0.052	-0.081	-0.024
	20-24		-0.124	-0.156 **	0.067	0.159 **	-0.031	0.047	-0.052	0.106	-0.015	
	25-29	-0.281 **	-0.198 ***	0.035	0.109 *	0.176 ***	-0.001	0.141	0.001	0.017		
	30-34	-0.034	-0.203 ***	-0.033	-0.044	0.094	0.001	-0.109 *	0.148 *			
	35-39	-0.104	-0.126 **	-0.043	0.039	0.123 *	0.038	0.019				
	40-44	-0.065	-0.201 ***	-0.121 *	0.006	0.083	0.009					
	45-49	-0.014 *	-0.099	-0.025	-0.049	-0.062						
	50-54	-0.133	-0.085	-0.071	0.005							
	55-59	-0.102	-0.099	0.016								
	60-64	-0.030	-0.181 *									
	65-69	-0.043										
	70-74											
	75-79											
	80-84											
	85-89											
	Step 2:											
Step 1:	Local F Test	2.427 *	8.650 ***	2.147 *	1.474	5.456 ***	0.300	2.405 *	2.345	1.387	0.384	na
Global F	**Step 3.1:**											
Test	Between	-0.090 ***	-0.146 ***	-0.042	0.005	0.069 *	0.020	0.018	0.081	0.023	-0.048	-0.024
2.647 ***	**Step 3.2:**											
	Intra-Cohort	0.116	0.043	0.005	-0.009	-0.023	-0.031	-0.032	-0.041	0.049	0.046	na

Note: Analysis includes GSS respondents who participated in the 1974 through 2012 GSS surveys in years in which POLVIEWS was administered and for whom POLVIEWS and year of birth are available. Figures reresent Iteratively reweighted least squares regression coefficients coded to sum to zero. Age and period coefficients are those presented in Table 4, Model 4. The global F test tests the hypothesis that taken together whether cohort effects exist. The local F test examines which cohort membership has an effect on political views. Between-cohort t tests look at the avarage effects of each cohort. Within-cohort tests investigate the linear trend in the life course of each cohort. ***=p<0.001 ; ** = p < 0.01 ; * = p < 0.05

Figure 1. Estimated Age, Period, and Cohort Trends in Political Views, General Social Survey, 1974-2012