A SIMULATION AND APPLICATION OF THE HIERARCHICAL AGE, PERIOD, COHORT MODEL

by

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(Under the Direction of Brian J. Hoffman)

ABSTRACT

The present studies extend research on generational effects in the workplace using the Hierarchical Age-Period-Cohort (HAPC) model. Using a Monte Carlo simulation, the first study examines how accurate generational effects estimated from cross-sectional data are. The results show that cross-sectional generational effect estimates are usually biased. It also extends methodological research on the HAPC model by demonstrating that the model can be used to estimate fixed generational effects, a fixed time trend effect, fixed generation × time period interactions, and fixed generation × age interactions. The second study applies the HAPC model to job satisfaction data obtained from the General Social Survey. The results show that employee job satisfaction is affected by their age, time period, and generation.

INDEX WORDS: Generation effects, Hierarchical age-period-cohort model, Job satisfaction

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DEDICATION

To my mother, Carole LoPilato. I would never have entertained the idea of graduate school if not for your gentle pushing and words of encouragement. Although you can no longer offer me your guidance, what you have instilled in me will continue to motivate me to be my best. I love and miss you.

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INTRODUCTION

Organizational and psychological science researchers, practitioners, and the popular press have increasingly sought to understand generational differences in the workplace and the potential effects of generational differences on a cross-section of organizational functions. Generations are commonly understood to be a distinct group of individuals born in a certain span of years that have experienced and been similarly impacted by a common set of historical and cultural phenomena (Lyons & Kuron, 2014; Mannheim, 1952; Parry & Urwin, 2011). Currently, individuals can belong to one of four generations: Silent Generation (1925-1942), Baby Boomers (1943-1960), Generation X (1961-1981), and Millennials (1982-Present; Parry & Urwin, 2011). Researchers and organizations want to know if employees who belong to different generations also hold different job attitudes and work values. For instance, research has concluded that that an employee's generational membership is associated with differences in organizational commitment (Smola & Sutton, 2002), work values (Jurkiewicz, 2000; Twenge, Campbell, Hoffman, & Lance, 2010), work ethic (Meriac, Woehr, & Banister, 2010), and job satisfaction (Kowske, Rasch, & Wiley, 2010).

On the basis of the research discussed above, many organizations have already started tailoring their core business processes such as recruitment (Chauhan, 2014; Puri, 2014), performance management (Brack, 2012; Puri, 2014), and training (Brack, 2012) to accommodate employees who belong to the Millennial generation (Costanza & Finkelstein, 2015). Yet, despite some evidence supporting generational differences in work-relevant constructs, research on generational differences in the workplace is plagued by a unique methodological problem, making it difficult to reach firm conclusions regarding how, if at all, generations differ on work-related constructs (Costanza & Finkelstein, 2015; Dencker, Joshi, & Marocchio, 2008; Glenn, 2005; Parry & Urwin, 2011).

This methodological problem is referred to as the Age-Period-Cohort (APC) confound and it describes a problem inherent to studies that use either cross-sectional or time-lag data to examine generational differences (Bell & Jones, 2014; Dencker et al., 2008; Glenn, 2005; Joshi, Dencker, & Franz, 2011). Specifically, to estimate and test generation effects it is necessary to control for age and period effects, which can manifest as generation effects or mask generation effects if left uncontrolled (Costanza & Finkelstein, 2015; Glenn, 2005; Gentile, Wood, Twenge, Hoffman, & Campbell, 2015; Yang & Land, 2008). Age effects “represent the variation associated with different age groups brought about by physiological changes, accumulation of social experience, and/or role or status changes” (Yang & Land, 2008, p. 298). Age effects capture physical and psychological changes that occur when an individual matures. Period effects represent variation associated with different time periods brought about by larger changes in the social, cultural, and physical environments (Yang & Land, 2008). Because period effects capture environmental changes they are thought to “affect all age groups simultaneously” (Yang & Land, 2008, p. 298).

In the study of age, period, and generation effects, a troublesome confound exists. Because an employee’s birth cohort is fully dependent on the time period they were surveyed and their age, or,

$$Cohort = Period - Age \quad (1),$$

only two of the three variables can be included in the same linear statistical model without transforming one of the variables in some way (Glenn, 2005). This confound makes it impossible to estimate a cohort effect while controlling for both an age and period effect. Moreover, this confound is exacerbated in cross-sectional data as an employee's age and birth cohort are perfectly correlated, making it impossible to estimate a continuous cohort effect while controlling for a continuous age effect. Although the APC confound is commonly referenced in studies comparing two or more birth cohorts—which is a group of individuals born within a certain span of time—it also applies to generational studies as generations encompass many different birth cohorts. Although the terms cohort and generation have been used interchangeably, I use the term generation if I am referring to one or all of the four generations and the term cohort if I am referring to a smaller birth cohort that is encompassed by one of the generations (Twenge, Campbell, & Carter, 2014).

Despite its relevance to studying generational differences, only a limited amount of organizational research has focused heavily on the APC confound, which is unfortunate as the majority of organizational research on generational differences in the workplace has based its conclusions on results obtained from cross-sectional data—which is data that is collected at a single time point from employees of different ages (Cenamo & Gardner, 2005; D'Amato & Herzfeldt, 2008; Dilworth & Kingsbury, 2005; Leiter, Jackson, & Shaughnessy, 2009). Indeed, a review of generational studies in the organizational literature revealed that at least 21 empirical articles have been published since 2000 and of those 21 articles 17 used cross-sectional designs (see Table 1). Moreover, of the 17 studies that used a cross-sectional design, 12 of those studies were published in 2008 or later.

Cross-sectional organizational research typically assigns an employee to a specific generation based on their age and then test for "generational" mean differences on an organizational variable. Such a test confounds age effects with generational effects, and does not allow for concluding anything about generational effects (Glenn, 2005). Alternatively, some organizational research has used time-lag data—which consists of cross-temporal data collected on employees of the same age at different time periods—to study generational effects (Twenge et al., 2010). As I discuss below, time-lag data can confound generational effects with time period effects (Gentile et al., 2015; Yang & Land, 2008).

In recognition of the confounds associated with both cross-section and time-lag studies of generational differences, methodological research has utilized a cross-classified random-effects model (CCREM) that analyzes repeated cross-sectional data—or cross-sectional data measuring the same variables that have been obtained periodically on different samples of individuals—called the Hierarchical Age-Period-Cohort (HAPC) Model (Yang & Land, 2006; 2008; 2013). However, despite its growing use in sociological and demographic research (Gauchat, 2012; Keyes, Schulenberg, O'Malley, Johnston, Bachman, Li, & Hasin, 2011; Masters, Hummer, & Powers, 2012; Reither, Hauser, & Yang, 2009; Yang, 2008), the HAPC model has received relatively little attention from organizational science, albeit with one exception (Kowske et al., 2010). Further, no research has sought to empirically examine the extent to which results obtained from cross-sectional data are actually biased. Research has also not examined how accurately the HAPC model estimates generational mean differences both when other effects such as period effects are present and when they are not present.

The primary purpose of this paper is to examine the extent to which generation effects estimated from cross-sectional data are accurate. It is important to know the extent to which results from cross-sectional studies are accurate as the majority of organizational research has based its conclusions about how generations affect job attitudes, values, and behaviors on cross-sectional data. Moreover, it is possible that the presence of other effects such as period effects could further affect cross-sectional generation effect estimates. To this end, the current paper provides the first methodological examination of the HAPC model in the management literature (Yang & Land, 2006; 2008; 2013). In doing so, it examines the extent to which cross-sectional estimates of generation effects differ from those obtained using the HAPC model. It also examines whether researchers can apply a reduced version of this model—which is a multilevel model (MLM)—to cross-sectional data to obtain more accurate estimates of generational and cohort effects than would be obtained from an ordinary least squares (OLS) regression model. Moreover, this paper extends methodological research on the HAPC model by determining how accurately the HAPC model can estimate generation effects in the presence of other effects such as age and period effects.

In the following sections, I first examine how the APC confound affects cross-sectional and time lag data, which has served as motivation for finding alternative statistical models to estimate generational and cohort effects. Next, I provide a conceptual and statistical introduction to the HAPC model and show how it offers organizational researchers the potential for more nuanced analyses of age, period, and generational effects. Specifically, I show that the HAPC model can simultaneously estimate a) fixed generation effects and random cohort effects, b) a time period effect, and c) interactions between generations and age as well as generation and time period. Following this, I conduct a simulation to determine how generation effects estimated from cross-sectional data using OLS regression as well as generation and cohort effects estimated using MLMs compare to effects estimated from repeated cross-sectional data using the HAPC model. By varying the effect sizes of the time period effect and the generational effects I can determine if and how the absence or presence of these effects biases the cross-sectional results. This variation also allows me to determine how well the HAPC model estimates generation effects when other effects are present. Finally, I provide a real data example by using the HAPC model to analyze job satisfaction data taken from the General Social Survey (GSS; Smith, Marsden, & Hout, 2015).

APC Confound and Cross-Sectional Designs

In this section I review the issues associated with using cross-sectional data to draw conclusions about generation effects. First, I show why researchers need to control for age when they are testing generation effects. I then argue against the practice of modeling age as a continuous predictor and generation as a categorical predictor in cross-sectional data (Costanza, Badger, Fraser, Severt, & Gade, 2012).

Although, conclusions about generational differences are commonly based on results from cross-sectional data, researchers are usually quick to point out that any generation or cohort trends should be interpreted with care (Costanza et al., 2012). This cautious interpretation is warranted. Given the perfect linear relationship between age and cohort shown in Equation 1, and assuming both effects are also linearly related to the dependent variable, then the following equation describes the data generation process:

$$Y = \beta_1 Age + \beta_2 Cohort \quad (2).$$

However, both age and cohort cannot be included in the same model due to their perfect linear relationship with one another. The researcher has two options to deal with this issue. The first option is to leave age uncontrolled for and test the following model:

$$Y = \beta_2 Cohort \quad (3).$$

Because the period effect is held constant in cross-sectional data, Equation 1 is reduced to:

$$Cohort = -Age \quad (4).$$

Equation 4 can then be substituted into Equation 2 and rearranged to derive Equation 5, which shows that if age is not controlled for then the estimated cohort effect will be a mixture of true age and cohort effects.

$$Y = (\beta_2 - \beta_1)Cohort \quad (5)$$

The problem is that, depending on the direction and magnitudes of the true age and cohort effects it is possible that a cohort effect may manifest when there is only a true age effect (β_1 > 0 or β_1 < 0 and β_2 = 0) or that a true cohort effect may be masked when the true age and cohort effects are equivalent in direction and magnitude (β_1= β_2).

The second option is to group different birth cohorts together to create generations to reduce the dependency of generational cohort membership and age. There are two problems with this solution. The first problem is that if cohorts have a continuous effect on the criterion variable, as some researchers have suggested (Lyons & Kuron, 2015; Twenge, 2010), then grouping together cohorts into a small number of large groups can lead to a reduction in power, incorrect effect size estimates, and other well documented statistical issues that occur when data is falsely categorized (MacCallum, Zhang, Preacher, & Rucker, 2002). However, as I discuss, this problem is only inherent to OLS regression models, not MLMs or the HAPC model. The second problem is that, logically, grouping together employees based on their birth cohorts is not different than grouping them together based on their ages. As a result, cohort groups that include employees with earlier birth years (e.g. 1940’s to 1950’s) will be older than cohort groups that include employees with later birth years making it impossible to determine if there is a cohort (generation) effect or a mean-age effect. That is, significant differences between groups could be attributed to either actual generational effects, mean age differences between the groups, or both; the effects still cannot be teased apart from each other. This problem plagues both OLS regression models and MLMs, but not the HAPC model.

Because neither neglecting to control for age nor grouping employees into larger generation groups are adequate solutions, organizational research on generational differences has usually argued that time-lag designs be used over cross-sectional designs (Gentile et al., 2015; Lyons & Kuron, 2014; Twenge et al., 2010). However, as I demonstrate in the following section, the APC confound can be just as damaging to time-lag designs as it can be to cross-sectional designs.

APC Confound and Time-Lag Designs

Time-lag designs are typically considered to be the gold standard for estimating and testing generation effects (Rhodes, 1983). This is because time-lag designs largely avoid confounding age effects with cohort effects as the design consists of employees of the same (or roughly the same) age sampled at different time periods. However, time-lag designs exchange the age-cohort confound for the period-cohort confound (Yang & Land, 2013). For example, if a researcher has job satisfaction measurements on four groups of 35 year old employees sampled from the years 1940, 1960, 1980, and 2000, respectively, then any differences between the job satisfaction measurements could be due to either the period the employees were sampled from or the cohort they belong to.

$$Cohort = Period \quad (6)$$

Despite this confound, organizational research willingly trades the age-cohort confound for the period-cohort confound as it is assumed that period effects are comparatively weak to cohort and age effects (Gentile et al., 2015; Twenge, 2010). This assumption allows researchers to safely conclude that the estimated cohort effect is an unbiased estimate of the true cohort effect. However, if period is substituted for age in Equations 2 through 5 it can be shown that the estimated cohort effect will be a mixture of both true period and cohort effects. Moreover, research is beginning to find that cohort and period effect sizes are of similar magnitudes, which cast doubts on the tenability of interpreting estimated cohort effects as unbiased estimates of true cohort effects (Kowske et al., 2010; Twenge et al., 2014; Twenge, Carter, & Campbell, 2015). This issue is made even worse as, unlike cross-sectional designs, there is no way to break the linear dependence between period and cohort in a time-lag design by creating generation groups because each period usually only contains a single birth cohort.

Thus, because of potential biases in both cross-sectional and time-lag designs, research on both cohort and generation effects has turned to the use of repeated cross-sectional designs, and more specifically, to the use of the HAPC model to estimate such effects (Kowske et al., 2010; Twenge et al., 2015; Reither et al., 2015; Yang & Land, 2006, 2008, 2013).

APC Confound and Repeated Cross-Sectional Designs

Repeated cross-sectional designs typify designs in which measurements are obtained periodically on different samples of individuals. Because the same individuals are not measured across each period, these designs differ from longitudinal designs. Moreover, because measurements are collected on a variety of individuals, birth cohorts vary both within and across time periods. For example, if the first sampled time period was 1970 and individuals between the ages of 18 and 65 were sampled then the birth cohorts would range from 1905 to 1952. If a new sample of individuals was obtained every year for several years there would be data covering many different cohorts at different time periods. That is, birth cohorts could be considered crossed, in the experimental sense, with time periods. This design is more advantageous than cross-sectional designs because there is age variance within a given cohort without having to group multiple cohorts together. It is also more advantageous than time-lag designs because it no longer confounds periods and cohorts. However, the repeated cross-sectional design does not resolve the APC confound by itself.

It is still impossible to fit a linear statistical model that controls for the continuous effects of age, period and cohort. However, because each cohort is now represented by a range of ages it is possible to separate cohort groups from age groups. Indeed, employees are now nested within the intersection of their birth cohort and time period. Because of this nesting, it is possible to analyze repeated cross-sectional data with a CCREM (Goldstein, 1994; Raudenbush & Bryk, 2002; Snijders & Bosker, 2011). CCREMs are similar to MLMs in that they allow for the level-one (L1) unit (persons) to be nested within a higher-level unit, often referred to as the level-two (L2) unit. CCREMs build on this by allowing the L1 unit to be nested within the intersection or crossing of two L2 units. Yang and Land (2006; 2008; 2013) recognized that CCREMs could be used to analyze data from repeated cross-sectional designs by treating employees (L1 unit) as nested within the crossing of their birth cohort and survey period (L2 units). When a CCREM is used to analyze APC data, it is often referred to as an HAPC model (Kowske et al., 2010; Reither, et al., 2015; Yang & Land, 2006, 2008, 2013). With an understanding of the pitfalls of cross-sectional and time-lag data, as well as the potential benefits of repeated cross-sectional data, I move on to a conceptual introduction of the HAPC model.

CHAPTER 2

AN OVERVIEW OF THE HAPC MODEL

Like MLMs, the HAPC model can partition the total dependent variable variance into several smaller variance components. Most research typically uses the HAPC model to partition the total dependent variable variance into an individual level variance component, a period variance component, and a cohort variance component (Yang & Land, 2006). Further, because age is an individual level variable it can be included in the HAPC model as a fixed-effect, which can be seen in the following equations:

$$L1\text{: } y_{ijk} = \beta_{0jk} + \beta_1 Age_{ijk} + e_{ijk} \quad (7)$$

$$L2\text{: } \beta_{0jk} = \gamma_0 + u_{0j} + u_{0k} \quad (8).$$

Equation 7 is the L1 model that shows that the dependent variable, y_{ijk}, is a function of the period, *k*, by cohort, *j*, mean (β_{0jk}), the fixed-effect of employee$_{ijk}$'s age (β_1), and an individual level residual, e_{ijk}, which reflects a random error that varies between persons. The L2 model, shown in Equation 8, shows that the L1 intercept, β_{0jk}, is a function of the grand mean of the dependent variable, γ_0, a period residual, u_{0k}, and a cohort residual, u_{0j}. The L2 residuals, u_{0k} and u_{0j}, are referred to as the random effects of period *k* and cohort *j*, respectively. Both L1 residuals, e_{ijk}, and L2 residuals, u_{0k} and u_{0j}, are all assumed to be independently and randomly distributed with a μ=0 and variances denoted here as σ^2, τ_{00k} and τ_{00j}, respectively. Although it is pedagogically useful to think of the HAPC model using Equations 7 and 8, the parameters of the model are estimated simultaneously using a single linear mixed-effects model (Putka, Ingerick, & McCloy, 2008):

$$\boldsymbol{Y} = \boldsymbol{X\beta} + \boldsymbol{Zu} + \boldsymbol{e} \quad (9),$$

where the $\boldsymbol{Y}, \boldsymbol{X}, \boldsymbol{\beta}$, and $\boldsymbol{e}$ matrices all have similar interpretations to the OLS regression model. However, there is no OLS regression analog for the $\boldsymbol{Z}$ and $\boldsymbol{u}$ matrices. The $\boldsymbol{Z}$ matrix is the random effects design matrix and contains dummy-coded variables that indicate the period and cohort groups that employees belong to. The $\boldsymbol{u}$ matrix contains both the period and cohort random effects.

Thus, the full HAPC model is able to estimate age, period and cohort effects because it specifies a fixed-effect for age and random effects for period and cohort. However, if research on generational differences in the workplace is going to adopt the HAPC model it is important that organizational researchers understand what effects the HAPC model can estimate and how accurate the subsequent estimates are under various data analytic scenarios.

Fixed Generation Effects versus Random Cohort Effects

Whereas the linear models that organizational researchers have previously used to estimate generation effects treat such effects as fixed (Becton, Walker, & Jones-Farmer, 2014; Hess & Jepsen, 2009; Smola & Sutton, 2002; Twenge et al., 2010), the HAPC model can treat a generation effect as fixed or random (Yang & Land, 2008). Fixed-effects are effects estimated from a factor whose "… levels in the study represent all possible levels of the factor or at least all levels about which inference is to be made" (Littell, Milliken, Stroup, Wolfinger, & Schabenberger, 2006, p. 4). That is, when treated as a fixed-factor, researchers are implicitly assuming that the four different generations are the only generations to which inferences are going to be made about and any estimated generation effect describes the relationship between the four different generations and the dependent variable (West, Welch, & Galecki, 2006).

Random effects are estimated from a random factor whose "…levels plausibly represent a larger population with a probability distribution" (Littell et al., 2006, p. 4). Said another way, the levels of a random factor (e.g. Silent, Boomer, X, and Millennials) are assumed to be sampled from a larger population of levels (e.g. a larger population of generations). Random effects are specific to a given factor level and represent "random deviations for a given subject or cluster from the overall fixed intercept" (West et al., 2006, p. 13). Indeed, random effects are comparable to OLS residuals and the interpretation of the random-effect variance is comparable to the interpretation of the residual variance component estimated by OLS models. So when generations are treated as a random factor, as they can be in the HAPC model, the generation effects represent the deviation of a specific generation's mean on a dependent variable from the overall dependent variable mean, which are residual deviations. Researchers can either interpret these deviations directly or use the estimated variance of these deviations to construct intraclass correlation coefficients (ICCs).

A problem with treating generations as random effects is that the four different generations typically exhaust all of the possible generations. Undoubtedly, different generational groups will be formed as time progresses, but currently four generations is enough to exhaust the theoretical population of generations. It does, however, make theoretical sense to treat birth cohorts as a random factor (Reither et al., 2015). Most organizational samples, cross-sectional or repeated cross-sectional, will only contain a sample of all possible birth cohorts. So, rather than separate generations into early, middle, and late categories (Kowske et al., 2010), organizational researchers should treat each cohort or a small grouping of cohorts as a level of a random cohort factor as is usually done in the sociological literature (Bell & Jones, 2014; Yang & Land, 2006, 2008, 2013). Organizational researchers can then treat generations as a fixed factor that accounts for systematic variance across the cohort random effects. This would allow organizational researchers to both construct pseudo-R^2 values as a measure of generation effect size (LaHuis, Hartman, Hakoyama, & Clark, 2014) and compare the results of generational differences from repeated cross-sectional data to those from cross-sectional data. Thus, our simulation will test the possibility of estimating both random-effects for cohorts and fixed-effects for generations.

Generational Interaction Effects.

Whereas most organizational research has focused on generational main effects, recent research has started testing for generation and age interactions (Becton et al., 2014). The HAPC model can test for this interaction and several other substantively interesting interactions. Although it is possible for generations to affect organizational variables both through an interaction with age and an interaction with time period, organizational research has been more concerned with the main effects of generations. Indeed, it is possible that generations interact with both an employee's and the time period (Becton et al., 2014; Yang, 2010). I describe each of these potential interactions below.

Generation × age interaction. The generation × age interaction suggests that the effect an employee's age exerts on an organizational criterion variable varies by the generation an employee belongs to. While this interaction effect can be tested in cross-sectional data (Becton et al., 2014) it is potentially biased as, by definition, each generation can only interact with a set range of ages in cross-sectional data. This same interaction effect can also be tested by the HAPC as the cross-level interaction between an employee's age and their generational membership (Bryk & Raudenbush, 2002; Snijders & Bosker, 2011). Because repeated cross-sectional data removes the age range constraint imposed by cross-sectional data, the HAPC model provides a potentially more accurate estimate of any true age by generation interaction. As this study is primarily concerned with determining the degree of bias in cross-sectional estimates of generational differences it does not examine the bias of generation × age interactions in cross-sectional data. The simulation does examine how the presence of a generation × age interaction affects cross-sectional mean generation differences and if the HAPC model can accurately estimate the generation × age interaction from repeated cross-sectional data.

Generation × period interaction. It is likely that a cohort's standing on most organizational variables has evolved differently over time than that of other cohorts. Yang (2010) and Yang and Land (2013) both described a theoretical continuously evolving cohort effects model where the effect of age varies over both time and cohorts. Indeed, this model is a continuation of early cohort analysis research that theorized that cohorts are continuously changing across time as they are exposed to various historical events (Hobcraft, Menken, & Preseton, 1982; Ryder, 1965; Yang, 2010). If cohorts are changing across time, then it is possible that generations are changing as well. This effect would be evidenced by a generation × period interaction.

The time period component of the HAPC model can be described by the following equation:

$$\beta_{0k} = \gamma_0 + u_{0k} \quad (10).$$

Equation 10 captures the relationship between the dependent variable averaged over all cohorts, β_{0k}, and the grand mean of the dependent variable, γ_0 (Yang & Land, 2006). That is, Equation 10 is a time series model known as a white noise process (Pickup, 2015). A white noise process is a simple time series model that assumes that there is no time trend in the data (i.e. stationary process) and that the error term, u_{0k}, is normally and identically distributed with a constant variance, τ_{00k}, assumptions identical to those the HAPC model makes about the random effects.

There are no issues with making these assumptions as long as neither theory nor the data indicate that the dependent variable is trending (changing) across time. However, research has shown and continues to show that psychological phenomena exhibit trends across time (Kalleberg & Marsden, 2013; Smith, Roberts, & Hulin, 1976; Twenge et al., 2015; Twenge et al., 2014). For instance, in an early study, Smith, Roberts, and Hulin (1976) found that employee job satisfaction exhibited a negative trend across three time periods (1963-1966, 1967-1970, and 1971-1972). More recently, Kalleberg and Marsden (2013) found trends in work values indicating that employees have started to place more importance on work that affords them a high income than they have on work that affords them opportunities for advancement, shorter work hours, and feelings of accomplishment. Moreover, research using the HAPC model has found evidence of time trends in the general public's trust in others (Twenge et al., 2014), confidence in institutions (Twenge et al., 2014), and tolerance for controversial beliefs and life styles (Twenge et al., 2015).

Although trends can be substantively interesting, they can cause methodological issues as the presence of a trend violates the assumptions made by the HAPC model. In order to control for the trend the researcher needs to identify the shape of the trend (e.g. linear, quadratic, quartic) and then include one or several polynomial time variables. For example, if a linear time trend was identified then it is only necessary to include a single variable, t, which ranges from 1 to the number of time periods, T. Thus, to understand if and how different generations are changing across time an organizational researcher could let the time trend variable(s) interact with the categorical generation variables. This simulation provides the first test of whether the HAPC model can adequately estimate a fixed time trend effect and an interaction between generations and period and how such effects impact the results from cross-sectional data.

Table 1. Previous Studies on Organizational Generational Differences

Year	Authors	Title	Design
2000	Jurkiewicz	Generation X and the public employee	Cross-Sectional
2001	Meuse, Bergmann, & Lester	An investigation of the relational component of the psychological contract across time, generation, and employment status	Cross-Sectional
2005	Dilworth & Kingsbury	Home-to-job spillover for generation X, boomers, and matures: A comparison	Cross-Sectional
2006	Davis, Pawlowski, & Houston	Work commitments of baby boomers and gen-Xers in the IT profession: Generational differences or myth?	Cross-Sectional
2007	Westerman & Yamamura	Generational preferences for work environment fit: Effects on employee outcomes	Cross-Sectional
2008	Beutell & Wittig-Berman	Work-family conflict and work-family synergy for generation X, baby boomers, and matures	Cross-Sectional
2008	Cenamo & Gardner	Generational differences in work values, outcomes and person-organisation values fit	Cross-Sectional
2008	D'Amato & Herzfedlt	Learning orientation, organizational commitment and talent retention across generations	Cross-Sectional
2008	Dries, Pepermans, & Kerpel	Exploring four generations' beliefs about career: Is "satisfied" the new "successful"?	Cross-Sectional
2008	Wong, Gardiner, Lang, & Coulon	Generational differences in personality and motivation: Do they exist and what are the implications for the workplace?	Cross-Sectional
2009	Hess & Jepsen	Career stage and generational differences in psychological contracts	Cross-Sectional
2009	Sullivan, Forret, Carraher, & Mainiero	Using the kaleidoscope career model to examine generational differences in work attitudes	Cross-Sectional
2011	Benson & Brown	Generations at work: Are there differences and do they matter?	Cross-Sectional
2012	Lub, Bijvank, Bal, Blomme, & Schalk	Different or alike? Exploring the psychological contract and commitment of different generations of hospitality workers	Cross-Sectional
2012	Park & Gursoy	Generation effects on work engagement among U.S. hotel employees	Cross-Sectional
2014	Becton, Walker, & Jones-Farmer	Generational differences in workplace behavior	Cross-Sectional
2014	Mencl & Lester	More alike than different: What generations value and how the values affect employee workplace perceptions	Cross-Sectional
2010	Kowske, Rasch, & Wiley	Millennials' (lack of) attitude problem: An empirical examination of generational effects of work attitudes	Repeated Cross-Sectional
2002	Smola & Sutton	Generational differences: Revisiting generational work values for the new millennium	Time-Lag
2010	Twenge, Campbell, Hoffman, & Lance	Generational differences in work values: Leisure and extrinsic values increasing, social and intrinsic values decreasing	Time-Lag
2014	Leuty & Hansen	Teasing apart the relations between age, birth cohort, and vocational interests	Time-Lag

CHAPTER 3

METHOD

Simulation Design and Data Generation

A simulation was designed to test all of the research questions. Using the programing language R (R Core Team, 2015), for each replication of the simulation a hypothetical criterion variable y_{ijk} for 57,000 respondents was generated according to the following model:

$$L1: y_{ijk} = \beta_{ijk} + \gamma_{01}Age + \gamma_{02}Age^2 + e_{ijk} \quad (11)$$

$$L2: \beta_{ijk} = \gamma_{00} + \gamma_{03}Time + \gamma_{04}Silent + \gamma_{05}X + \gamma_{06}Mill + \gamma_{07}Age * Silent + \gamma_{08}Age * X + \gamma_{09}Age * Mill + \gamma_{010}Time * Silent + \gamma_{011}Time * X + \gamma_{012}Time * Mill + u_{0j} + u_{0k} \quad (12),$$

where *Age* was sampled from a normal distribution with μ=45.70, σ=17.47, with the constraint that the distribution was truncated to have a lower bound of 18, and an upper bound of 89. The *Time* (or "period") variable was simulated from a uniform distribution with a lower bound of 1972 and an upper bound of 2012. The *Cohort* variable was created by subtracting the age variable from the period variable to obtain the birth year of the respondent, which simulates the real-world dependency shown in Equation 1.

Using the *Cohort* birth year variable, each simulated case was categorized as belonging to one of four generations: a) those with birth years between 1883 and 1942 were categorized as a Silent Generation member; b) those with a birth year between 1943 and 1960 were categorized as a Baby Boomer; c) those with a cohort value between 1961 and 1981 were categorized as Generation X; and d) those with a cohort value between 1982 and 1994 were categorized as Millennials (Parry & Urwin, 2011). The period, cohort, and individual level residuals were each simulated from independent normal distributions with means of zero and variances of .01, .01, and 1.38, respectively. All of the above values were based on descriptive statistics obtained from the General Social Survey (GSS) and previous generational and cohort research that has used the HAPC model (Kowske et al., 2010; Twenge et al., 2014, 2015; Yang & Land, 2006, 2008) to approximate real-world data analytic conditions.

In order to answer the research questions I manipulated four simulation factors. The first manipulated factor was the average effect size of the generation main effects. The second manipulated factor was the effect size of the time trend. The third manipulated factor was the average effect size of the generation × age interactions, which had three levels. The fourth manipulated factor was the average effect size of the generation by time interactions, which had three levels. The main and quadratic effects of age and the cohort, period, and individual-level residuals were held constant across all of the simulation conditions. This simulation design resulted in 72 different conditions that were each simulated 100 times. The simulation parameters can be found in Table 2. Although the simulation factors are crossed, they differ in the number of levels in order to maintain a manageable number of simulation conditions. Moreover, the parameters provided in Table 2 are not standardized, but were selected so that when standardized small, medium, and large effects will be roughly equal to .10, .30, and .50, respectively. Standardized values were not used to generate the data because the values used to simulate the cohort, period, and residual variance components were obtained from non-standardized variance component estimates reported in several empirical studies (Kowske et al., 2010; Yang & Land, 2006).

To determine the extent to which results obtained from cross-sectional data differ from those obtained from repeated cross-sectional data I analyzed each yearly cross-section of the simulated repeated cross-sectional data. For example, to determine how accurate generation effect estimates were for the year 2000, cases belonging to the year 2000 were selected from the larger repeated-cross sectional database and generation effects were estimated. This was repeated for all of the simulated years.

To determine the accuracy with which the HAPC model is able to estimate generation fixed-effects, generation $\times$ age interactions, time period trend, and a generation by time period trend interaction I calculated bias, root mean squared error (RMSE), and Type 1 error statistics. I then conducted an Analysis of Variance (ANOVA) to determine the extent to which these statistics differed by simulation condition. Finally, the results of this simulation will be used to inform the empirical study.

Table 2. Simulation Parameters

Simulation Parameters Constant Across All Simulations					
Cohort Variance	.01				
Period Variance	.01				
Level 1 Variance	1.38				

Simulation Parameters Varied Across Simulations					
Generation Mean Differences		No Effect	Small Effect	Medium Effect	Large Effect
	Silent	.00	1.10	1.88	2.42
	X	.00	1.40	2.37	3.06
	Millennial	.00	3.97	6.77	8.73
Linear Period Trend					
		.00		.08	
Period x Generation Interactions					
	Period by Silent	.00	.06	.10	
	Period by X	.00	.11	.19	
	Period by Millennial	.00	.25	.42	
Age x Generation Interactions					
	Age by Silent	.00	.06	.10	
	Age by X	.00	.08	.14	
	Age by Millennial	.00	.16	.27	

Note. For all generation mean comparisons the Boomer generation was used as the reference group.

CHAPTER 4

SIMULATION RESULTS

The Type 1 error rates can be found in Table 3. These rates convey the proportion of times a significant main effect for the generational comparisons was found even though the data were simulated without such effects. The optimal Type 1 error rate will be at or around the nominal alpha rate, which was set at .05. Table 3 shows that researchers analyzing cross-sectional data will falsely reject the null hypothesis that there is no generational main effect around 77% of the time; a rate much higher than the accepted .05 cut-off. Similarly unacceptable rates were also found for the HAPC estimates when the generational main effects were tested using Type II sums of squares.

Acceptable rates were only found for the HAPC estimates when Type III sums of squares were used. Briefly, Type III sums of squares tests each generational main effect while controlling for any specified generational interactions, whereas the Type II sums of squares does not (Langsrud, 2003). In fact, across all three models it appears that when generation does not interact with either period or age (Simulation Conditions 1 and 10) each model displays acceptable Type 1 error rates. This suggests that the interactions of generation with both period and age play a potential role in introducing error in the detection of generational effects.

Table 4 contains the parameter estimates, bias, and RMSE of the generational mean comparisons averaged across all 72 simulation conditions obtained from the OLS, HLM, and HAPC models. Across all three generational mean comparisons the bias in the OLS and HLM estimates becomes progressively worse, with the least amount of bias seen in the Boomer-Silent

Generation comparison (.00 and -.04, respectively) and the most amount of bias seen in the Boomer-Millennial Generation comparison (1.28 and 1.32, respectively). The HAPC model was able to estimate the three generational mean comparisons with little to no bias (.00 - .02). Indeed, the average bias across parameter estimates for the OLS and HLM models was .25 and .27, respectively, whereas the average bias for the HAPC model was .01. That is, both the OLS and HLM models are overestimating generational effects, whereas the HAPC is accurately estimating the effects.

The RMSE seen in the generational mean comparisons displays the same general pattern. RMSE in OLS estimates ranged from 1.22 for the Boomer-Silent comparison to 3.12 for the Boomer-Millennial comparison and RMSE in the HLM estimates range from 1.33 for the Boomer-Silent comparison to 3.48 for the Boomer-Millennial comparison. RMSE in the HAPC estimates is smaller in comparison to the OLS and HLM estimates, ranging from .05 to .66. It shows that the RMSE shows that the HAPC estimates the Boomer-Millennial mean comparison with less accuracy then the other two comparisons. Overall, the average RMSE of OLS estimates is 7.57 times larger than the average RMSE of HAPC estimates and the average RMSE of HLM estimates is 8.39 times larger than the average RMSE of HAPC estimates.

In order to determine the effect that the various simulation conditions and their interactions had on the bias and RMSE of each model's generational mean comparisons I first estimated an analysis of covariance (ANCOVA) model that contained the main effects of each simulation factor and controlled for the continuous effect of the average generation sample size. Because the sample size of each generation varied slightly across each simulation condition it is possible that if sample size was left uncontrolled for then simulation condition differences could actually reflect sample size differences. I then tested the model that contained the simulation condition main effects against models that included higher-order interactions among all of the simulation conditions. The most parsimonious model that adequately captured the effects of each simulation condition was accepted.

For both the OLS and HLM models, the bias in each of the generational mean comparisons was affected by the generation × period interaction factor and the generation × age interaction factor. Those factors as well as their interaction affected the RMSE of the generational mean comparisons. Models containing higher-order interactions did not explain additional variance beyond the models containing the two-way factor interactions. The bias and RMSE of generational mean comparisons obtained from the HAPC model were not strongly affected by any of the simulation conditions or their interactions.

Focusing on the bias in the Boomer-Silent generational mean comparison first, the simulation conditions had no impact on the bias when the mean comparison was estimated by OLS regression. The bias present in the mean comparison when estimated by HLM was significantly affected by the generation × age interaction factor ($F_{2, 62} = 1124.14$, $p < .01$). Next, for both the OLS and HLM models, the bias present in the Generation X-Baby Boomer mean comparison was significantly affected by the generation × period interaction factor ($F_{2, 62} = 57{,}530.00$, $p < .01$ and $F_{2, 62} = 56{,}560.00$, $p < .01$, respectively) and the generation × age interaction factor ($F_{2, 62} = 352{,}600.00$, $p < .01$ and $F_{2, 62} = 312{,}900.00$, $p < .01$, respectively). Similarly, the bias present in the Millennial-Baby Boomer comparisons estimated from the OLS and HLM models were significantly affected by the generation × period ($F_{2, 62} = 1.23 \times 10^6$, $p < .01$ and $F_{2, 62} = 1.20 \times 10^6$, $p < .01$, respectively) and generation × age interaction factors ($F_{2, 62} = 426{,}200.00$, $p < .01$ and $F_{2, 62} = 397{,}800$, $p < .01$, respectively). Across all three mean comparisons the bias changed in identical patterns across the OLS and HLM estimates.

Specifically, as the effect size of the generation × period interaction increased the generational mean comparisons were increasingly overestimated (i.e. positive bias) and as the effect size of the generation × age interaction increased the generational mean comparisons were increasingly underestimated (i.e. negative bias).

As for the RMSE of the different mean comparisons, the two-way interactions for each generation mean comparison were plotted in Figures 1 through 3. For the purposes of comparison, each figure contains three interaction plots depicting the effect that the two-way interaction has on the RMSE of OLS estimates, HLM estimates, and HAPC estimates. Because the effects of the two-way interaction on the RMSE of the OLS and HLM estimates were nearly identical I only compare the OLS results to the HAPC results. First, Figure 1 shows that the RMSE present in the OLS Boomer-Silent generational mean comparison increases from a low of .17 when there is neither a generation × age interaction nor a generation × period interaction to a high of 2.27 when there is a medium effect for both the generation × age and generation × period interactions ($F_{32, 39}$ = 95,380.00, $p < .01$). The RMSE of the same generation mean comparison estimated from the HAPC model is unaffected by the magnitude of either interaction and is never greater than .06 ($F_{32, 39}$ = 1.41, $p > .05$). Next, Figure 2 shows that the RMSE present in the OLS Boomer-X generational mean comparison increases from a low of .21 when there is neither a generation × age interaction nor a generation × period interaction to a high of 3.54 when there is a medium effect for both the generation × age and generation × period interactions ($F_{32, 39}$ = 76,970.00, $p < .01$). In contrast, the RMSE of the same generation mean comparison estimated from the HAPC model is unaffected by the magnitude of either interaction and is never greater than .13 ($F_{32, 39}$ = 1.04, $p > .05$). Finally, Figure 3 shows that the RMSE present in the OLS Boomer-Millennial generational mean comparison increases from a low of

.35 when there is neither a generation × age interaction nor a generation × period interaction to a high of 6.07 when there is no generation × age interaction, but there is a medium generation × period interaction effect ($F_{32, 39} = 41{,}200.00$, $p < .01$). The RMSE of the same generation mean comparison estimated from the HAPC model is unaffected by the magnitude of either interaction and is never greater than .72 ($F_{32, 39} = .70$, $p > .05$).

In comparison to the HAPC estimates, it seems that both OLS and HLM inaccurately estimate generational mean comparisons in the presence of generational interactions. To determine how accurately OLS and HLM estimate generational mean comparisons when such interactions are not present, average across simulation parameter estimates, bias, and RMSE were calculated for conditions that did not specify any generational interactions. These results can be found in Table 5, which shows that the bias and RMSE found in cross-sectional estimates of generational mean differences are actually smaller than those estimated from repeated cross-sectional data. However, because RMSE seen in cross-sectional generational mean comparison estimates increases in the presence of generation × age and generation × period interactions it is important to know if the HAPC model can accurately estimate these effects.

Table 6 contains the average across simulation parameter estimates, bias, RMSE, and Type 1 error rates for the period trend effect, generation × period interaction effects, generation × age interaction effects, and the L1 and L2 variance components. The results show that the HAPC model was able to estimate each effect with minimal bias and very small RMSE (.01 to .02). Indeed, the HAPC model was able to estimate these higher-order effects with less bias and RMSE than the generational mean comparisons. The average Type 1 error rates were also found to be in acceptable ranges (.05 - .07 across all effects). Moreover, the simulation factors did not strongly affect the parameter bias or RMSE for any of the estimated parameters.

Table 3. Type 1 Error Rates for Generational Comparisons

	Model											
	OLS			HLM			HAPC					
Condition	B-S	B-X	B-M	B-S	B-X	B-M	B-S (T3)	B-X (T3)	B-M (T3)	B-S (T2)	B-X (T2)	B-M (T2)
1	.07	.08	.07	.06	.06	.06	.05	.08	.07	.04	.08	.08
2	.65	.81	.98	.58	.76	.97	.01	.05	.06	.13	1.00	1.00
3	.77	.89	1.00	.66	.82	1.00	.11	.08	.12	.52	1.00	1.00
4	.77	.81	.99	.76	.80	.99	.07	.07	.05	1.00	1.00	1.00
5	.86	.92	.73	.81	.91	.68	.07	.05	.05	1.00	.45	.04
6	.88	.94	.84	.80	.90	.75	.06	.03	.05	1.00	1.00	1.00
7	.88	.89	1.00	.87	.89	1.00	.07	.08	.07	1.00	1.00	1.00
8	.90	.94	.90	.87	.93	.90	.05	.04	.06	1.00	1.00	1.00
9	.91	.96	.84	.86	.93	.75	.06	.07	.06	1.00	.82	.12
10	.07	.06	.06	.06	.05	.05	.08	.07	.04	.07	.04	.04
11	.66	.81	.97	.59	.76	.96	.10	.08	.07	.20	1.00	1.00
12	.77	.89	1.00	.67	.82	1.00	.07	.08	.04	.34	1.00	1.00
13	.78	.81	.99	.76	.80	.99	.10	.06	.06	1.00	1.00	1.00
14	.86	.93	.73	.82	.90	.68	.04	.09	.03	1.00	.45	.05
15	.88	.94	.84	.80	.90	.74	.05	.04	.02	1.00	1.00	1.00
16	.88	.89	1.00	.87	.88	1.00	.06	.08	.06	1.00	1.00	1.00
17	.90	.95	.90	.87	.93	.89	.13	.05	.08	1.00	.99	1.00
18	.91	.96	.85	.86	.92	.77	.09	.08	.04	1.00	.81	.16
Average	.74	.80	.82	.70	.76	.79	.07	.07	.06	.74	.81	.69

Note. B = Boomer Generation; S = Silent Generation; X = Generation X; M = Millennial Generation; T2 = Type 2 Sum of Squares; T3 = Type 3 Sum of Squares.

Table 4. Average Parameter Bias and RMSE across all Simulations

	Model	$\gamma_{04,\text{Silent}}$	$\gamma_{05,\text{X}}$	$\gamma_{06,\text{Millennial}}$	Average Across Parameter
Estimate	OLS	1.35	1.19	5.14	
	HLM	1.31	1.23	5.18	
	HAPC	1.35	1.71	3.89	
Bias	OLS	.00	-.52	1.28	**.25**
	HLM	-.04	-.48	1.32	**.27**
	HAPC	.00	.00	.02	**.01**
	Average	**-.01**	**-.33**	**.87**	
RMSE	OLS	1.22	2.02	3.12	**2.12**
	HLM	1.33	2.24	3.48	**2.35**
	HAPC	.05	.12	.66	**.28**
	Average	**.87**	**1.46**	**2.42**	

Note. OLS = Ordinary Least Squares Regression; HLM = Hierarchical Linear Model; HAPC = Hierarchical Age, Period, Cohort Model; RMSE = Root Mean Squared Error.

Table 5. Average Parameter Bias and RMSE with No Generational Interactions

		Parameter			
		$\gamma_{04,\text{Silent}}$	$\gamma_{05,\text{X}}$	$\gamma_{06,\text{Millennial}}$	Average Across Parameter
	Model				
Estimate	OLS	1.35	1.70	3.87	
	HLM	1.35	1.70	3.87	
	HAPC	1.35	1.71	3.90	
Bias	OLS	.00	.00	.00	**.00**
	HLM	.00	.00	.00	**.00**
	HAPC	.00	.00	.04	**.01**
	Average	**.00**	**.00**	**.01**	
RMSE	OLS	.17	.21	.35	**.24**
	HLM	.17	.21	.35	**.24**
	HAPC	.05	.12	.66	**.28**
	Average	**.13**	**.18**	**.45**	

Note. OLS = Ordinary Least Squares Regression; HLM = Hierarchical Linear Model; HAPC = Hierarchical Age, Period, Cohort Model; RMSE = Root Mean Squared Error.

Table 6. Average Bias and RMSE for HAPC Model Parameter Estimates

	γ_{03},Period	γ_{07},Period x Silent	γ_{08},Period x X	γ_{09},Period x Millennial	γ_{010},Age x Silent	γ_{011},Age x X	γ_{012},Age x Millennial	τ_{00j}	τ_{00k}	σ^2
Estimate	.04	.05	.10	.22	.05	.07	.14	.01	.01	1.38
Bias	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
RMSE	.01	.01	.01	.02	.01	.01	.02	.00	.00	.00
T1 Error	.06	.06	.07	.05	.06	.06	.05			

Note. RMSE = Root Mean Squared Error; T1 Error = Type 1 Error; X = Generation X.

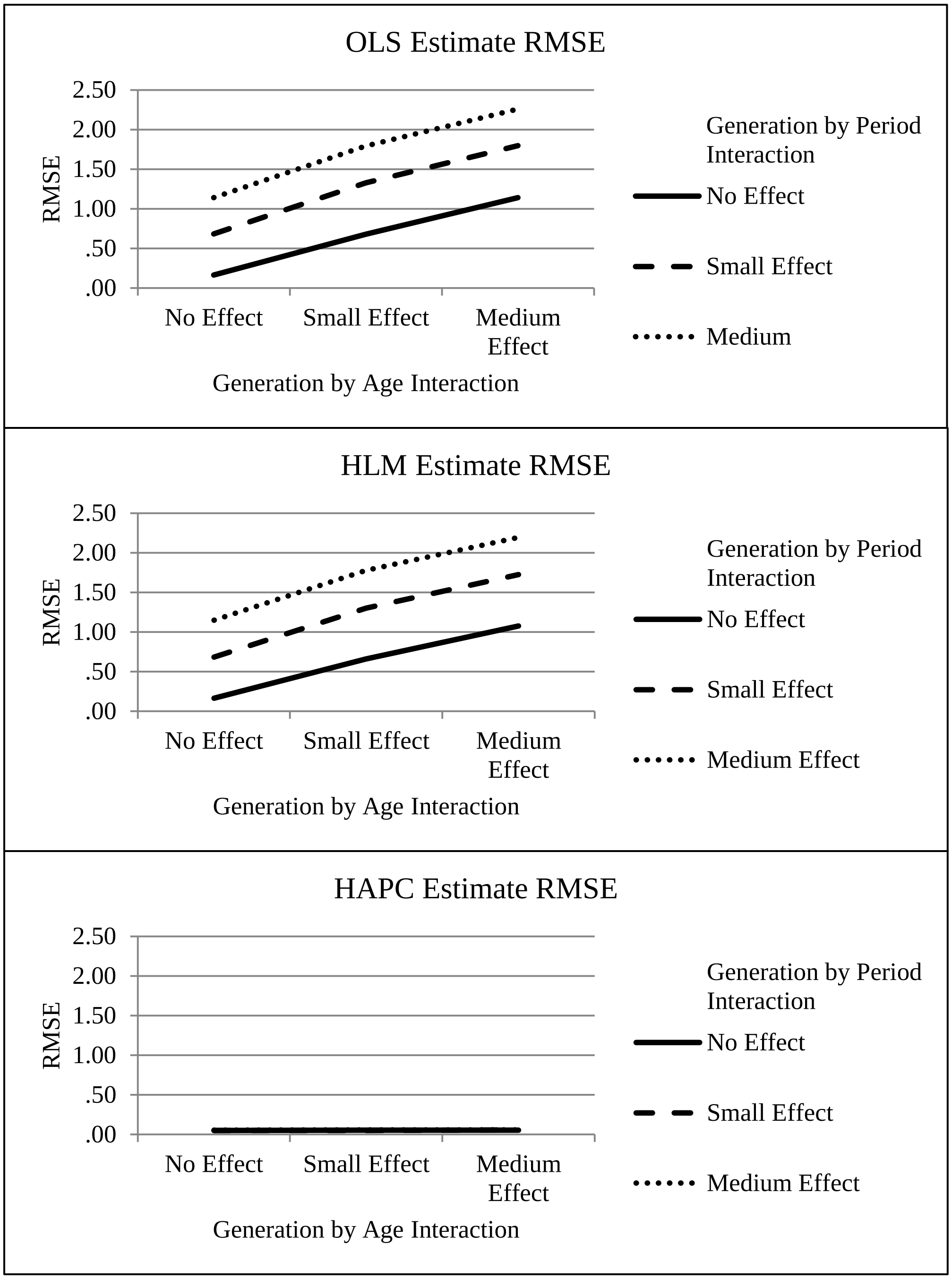

Figure 1. RMSE of Boomer Generation – Silent Generation Comparison

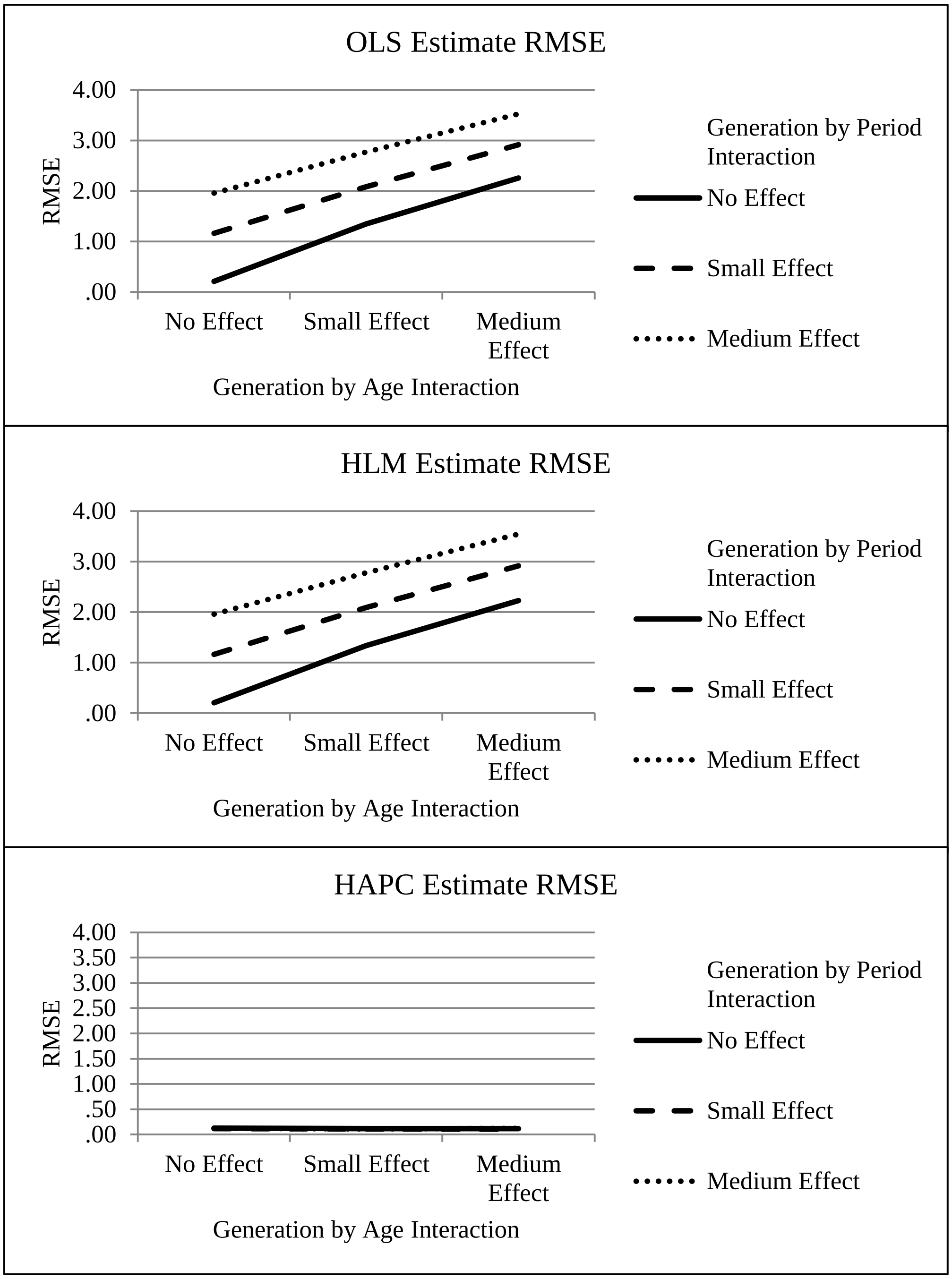

Figure 2. RMSE of Boomer Generation – Generation X Comparison

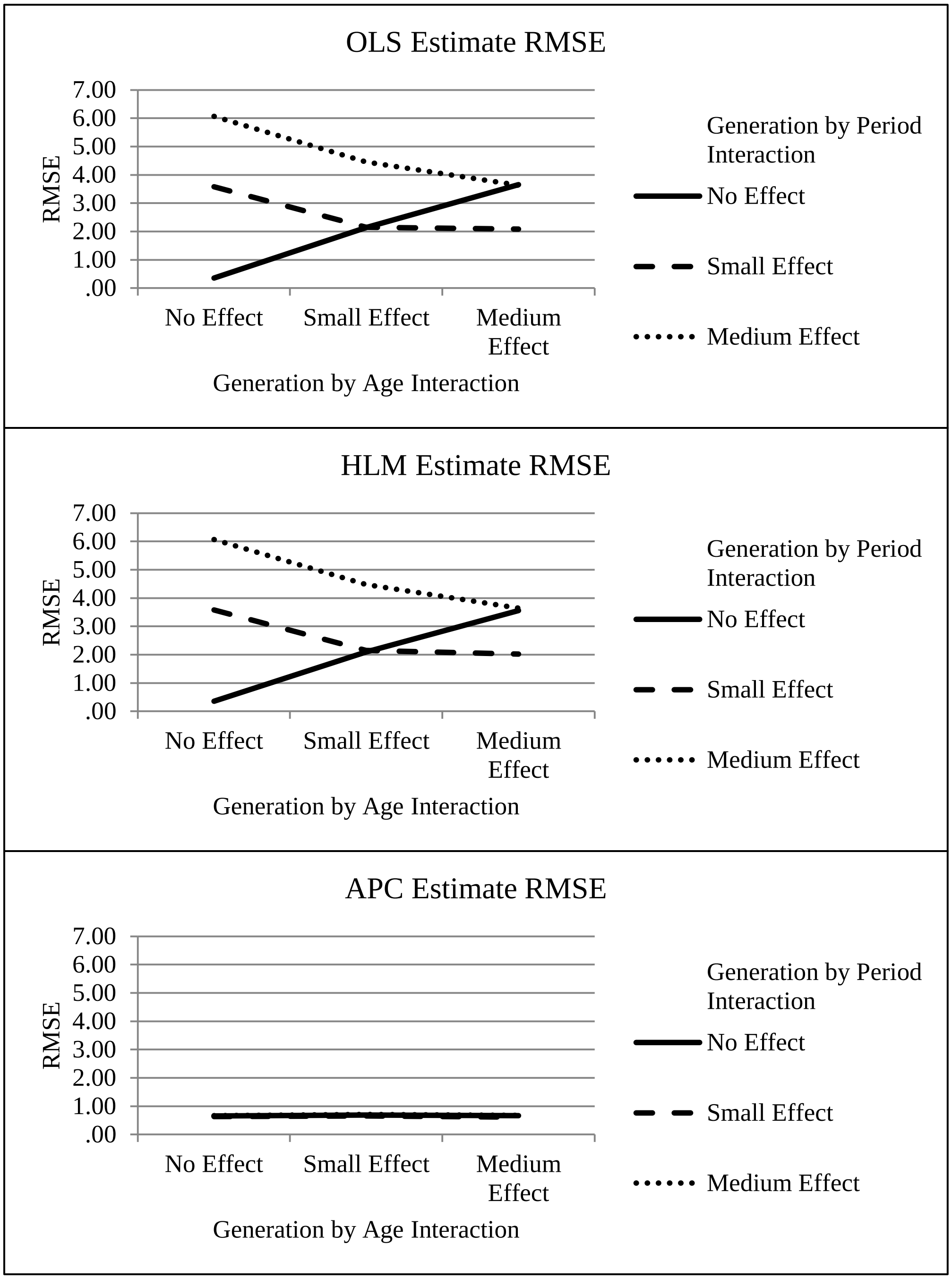

Figure 3. RMSE of Boomer Generation – Millennial Generation Comparison

CHAPTER 5

SIMULATION STUDY DISCUSSION

The purposes of this simulation study were to determine a) how biased cross-sectional estimates of generational mean comparisons were in comparison to estimates obtained from repeated cross-sectional data and b) the extent to which the HAPC model can estimate a period trend effect, generation $\times$ period interactions, and generation $\times$ age interactions. This study provided several important findings. First, in comparison to repeated cross-sectional data, generational mean comparisons estimated from cross-sectional data were generally inaccurate except when generations did not interact with either period or age effects. Second, the pattern present in the bias suggests that age and period effects exert an oppositional influence over estimates of generational mean comparisons. Finally, the HAPC model was able to accurately estimate a period trend effect, generation $\times$ period interactions, and generation $\times$ age interactions.

Cross-Sectional Estimates versus Repeated Cross-Sectional Estimates

A common theme across cross-sectional research on generational differences is the recognition that generational effects are confounded with age effects (Lyons & Kuron, 2014; Parry & Urwin, 2011; Twenge, 2010). Because of this confound it is impossible to know if the generational mean comparisons are overestimates of true effects, underestimates, or non-existent.

Indeed, researchers should be concerned with the accuracy of cross-sectional generational mean comparisons when there is reason to believe that the dependent variable is affected by an interaction between generations and age, generations and time period, or both. These interactions inflate the Type 1 error rate from .05 to an average of .88, meaning that when there are no generational main effects, 88% of the time a researcher will reject the null hypothesis rather than the accepted 5%. In comparison, when these generational main effects are estimated from the HAPC model along with the various generational interactions and tested using Type III sum of squares then the average Type 1 error rate was found to be .06, which is much more acceptable. Following this result, it is recommended that when testing the significance of the age, generation, and period main effects in the presence of generational interactions that Type III sum of squares be used. Indeed, most commercial statistical analysis software such as SAS and SPSS use Type III sum of squares as their default (Langsrud, 2003). The downside to using Type III sum of squares over the other two types is that it reduces the power of one's tests (Langsrud, 2003).

Beyond Type 1 error rates, the presence of generational interactions caused cross-sectional estimates of generational effects to be inaccurately estimated. Across all three cross-sectional comparisons the average RMSE was 2.12 when estimated by OLS and 2.35 when estimated by HLM. When these same comparisons were estimated from repeated cross-sectional data the average RMSE was only .28. Moreover, as Figures 1-3 show, the RMSE in cross-sectional estimates of generational effects increases greatly when both the generation $\times$ age and generation $\times$ period interactions are present. Unfortunately, it does not matter whether the cross-sectional estimates are obtained using OLS or HLM as both models provide inaccurate estimates. Generational effects estimated from repeated cross-sectional data, however, are not adversely affected by this interaction.

If neither interaction is present then it is possible to estimate accurate generational effects from cross-sectional data. That is, in the conditions where the data was simulated from a model that did not specify either interaction the Type 1 error rates for cross-sectional estimates ranged from .07 to .08, which were very similar to the Type 1 error rates for the repeated cross-sectional estimates which ranged from .05 to .08. The average cross-sectional estimate bias and RMSE (.00 and .24, respectively) were both lower than the average repeated cross-sectional estimate bias and RMSE (.24 and .28, respectively). These findings strongly suggest that when there are no higher-order effects such as the generational interactions, then generational effects estimated from cross-sectional data can actually be trusted. This finding is further strengthened by the fact that the cross-sectional effects were accurately estimated even when an age main effect and quadratic effect were present.

Unfortunately, theoretical research on organizational generational effects is still sparse, so the extent to which generation × age and generation × period interactions are present is still unclear. Moreover, estimates from cross-sectional data can be negatively affected even if only one kind of interaction is present.

Opposing Effects of Age and Period

Focusing on Table 4, one of the first things to note is the discrepancy between the bias and RMSE indices for all three models. For instance, the bias for the Boomer-Silent generation cross-sectional OLS estimate is .00, but the RMSE is 1.22. This discrepancy indicates that in some simulation conditions the Boomer-Silent generation comparison is overestimated and in other conditions it is underestimated. When the over and underestimates are averaged together to calculate the bias index they average out to zero. Unlike the bias index, the RMSE measures the extent to which the estimates vary around the true parameter by squaring the difference between the model estimate and the true parameter.

In the context of this study, the APC confound offers a clear explanation as to when generational comparisons will be overestimated and when they will be underestimated.

Specifically, Equation 1 shows that Generation, which is substituted for Cohort, is negatively related to Age and positively related to Period. This results in an underestimation of cross-sectional estimates of generational effects when generation only interacts with age and an overestimation when generation only interacts with period. Indeed, the simulation results show that when only a generation × age interaction was present the bias in the cross-sectional Boomer-X comparison was -.83 for OLS and -.86 for HLM and the bias in the Boomer-Millennial comparison was -1.78 for OLS and -1.82 for HLM. In contrast, when only a generation × period interaction the bias for the Boomer-X comparison was .35 for OLS and HLM and the bias for the Boomer-Millennial comparison was 3.10 for OLS and HLM. The bias for the Boomer-Silent comparison was found to be zero, regardless of which effect was present. However, the average RMSE for the Boomer-Silent comparison indicates that even within a condition the estimated generational effects varied widely.

Thus, the presence of even one type of generational interaction is enough to severely bias cross-sectional generational effect estimates. Because of this it is important to determine which organizational variables are affected by such interactions. However, before research can do this it is important to know how well the HAPC model can estimate these different effects.

Estimation of Period and Generational Interactions

Beyond estimating generational main effects, the HAPC model offers researchers the ability to estimate a period trend as well as interactions between generations and age and period, respectively. In fact, the HAPC model is currently the only model that can simultaneously estimate all of the above effects from repeated cross-sectional data. However, previous literature has yet to estimate and test any of these effects using the HAPC model. One potential reason for this is that until now no studies have investigated how well the HAPC model can estimate these effects. Addressing this gap, this study found that the HAPC could accurately estimate a period trend, generation × age interactions, generation × period interactions, the L1 residual, and the L2 residual.

Indeed, the HAPC model was able to more accurately estimate these effects compared to the generational main effects. This can be easily seen by comparing the RMSE of the different effects. For the generational main effects, the RMSE ranged from .05 for the Boomer-Silent Generation mean comparison to .66 for the Boomer-Millennial mean comparison whereas the RMSE for the remaining effects ranged from .01 to .02. Further, the average Type 1 error rates for all of the estimated fixed effects ranged from .05 to .07, which indicates that researchers should not be overly concerned with committing a Type 1 error when interpreting the HAPC estimates.

Conclusion

Overall, the simulation results suggest that the HAPC is able to accurately identify and estimate a period trend and higher-order interactions. This is important because if the interactions are present then researchers should not draw generational inferences from cross-sectional data, which draws into question results that are based on cross-sectional data (see Table 1). Moreover, the only way to be certain that such effects are present is to estimate and test them using the HAPC model. With this established, I move onto the second study in which I investigate whether or not generations differ on their job satisfaction and if job satisfaction is affected by any generational interactions.

CHAPTER 6

STUDY 2: THE CASE OF JOB SATISFACTION

Job attitudes are and have always been one of the most popular research topics of organizational psychology (Judge & Kammeyer-Mueller, 2012). They have been defined as "evaluations of one's job that express feelings toward, beliefs about, and attachment to one's job" (Judge & Kammeyer-Mueller, 2012, p. 343), and they can be broken down into more discrete attitudes such as job satisfaction, organizational commitment, and attitudes towards specific behaviors. Of these different discrete job attitudes, job satisfaction has received the greatest amount of research attention. It is defined as "an evaluative state that expresses contentment with and positive feelings about one's job" (Judge & Kammeyer-Mueller, 2012, p. 343).

Organizational research on job satisfaction has found that an employee's job satisfaction is related to many important organizational criterion variables such as task performance (Judge, Thoresen, Bono, & Patton, 2001), citizenship behaviors (Hoffman, Blair, Meriac, & Woehr, 2007; Ilies, Fulmer, Spitzmuller, & Johson, 2009; Ilies & Judge, 2002), counterproductive work behaviors (Dalal, 2005), organizational performance (Harter, Schmidt, & Hayes, 2002), and a variety of worker health outcomes (Faragher, Cass, & Cooper, 2005). As one of the preeminent management constructs, it is natural that researchers have sought to understand how job satisfaction has changed over time and across generations. In doing so, researchers have employed different measurement designs to test how job satisfaction changes with age, time period, and generational membership. Indeed, it has been the focus of cross-sectional, longitudinal, and repeated cross-sectional research (Costanza et al., 2012; Judge & Kammeyer-Mueller, 2012; Kowske et al., 2010; Ng & Feldman, 2010; Smith et al., 1976).

Although mixed, there is evidence that age, period, and generation influence a worker's job satisfaction (Bowling, Hoepf, & LaHuis, 2013; Costanza et al., 2012; Kalleberg, 2013; Kooij, Jansen, Dikkers, & De Lange, 2009; Kowske et al., 2010; Ng & Feldman, 2010; Smith et al., 1976). While these previous studies have given the field of organizational psychology an idea of how age, period, and generations affect job satisfaction, it is difficult to safely conclude that those studies are actually estimating and testing pure age, period, or generational effects. With the exception of Kowske et al. (2010), cross-sectional research has been used to obtain meta-analytic relationships between age and job satisfaction (Ng & Feldman, 2010) as well as the relationships between generational membership and job satisfaction (Costanza et al., 2012). This research has potentially confounded age and generation effects (Gentile et al., 2015; Yang & Land, 2013). Comparatively, most research examining temporal changes in job satisfaction has potentially confounded period and generation effects (Gentile et al., 2015). Indeed, it is possible that much of what I know about the effects of age, period, and generations on job satisfaction is wrong.

Because of job satisfaction's relationships with relevant organizational criterion variables it is important for organizations to know if job satisfaction is being affected by age, period, and/or generation effects. Knowing this information could help organizations develop more effective interventions for increasing an employee's job satisfaction. For instance, if employees who belong to Generation X are more satisfied than those who belong to the Millennial generation, then an organization could develop a new intervention to specifically target employees who belong to the Millennial generation (Costanza et al., 2012). Alternatively, if differences in job satisfaction are actually between-age differences such that older employees are more satisfied with their job than younger employees then the organization might be able to rely on an already developed intervention that worked with past younger employees. Finally, a time period effect would entail that every employee was less (or more) satisfied than in past years, which could signal to the organization that a large intervention that affects every employee is necessary (or unnecessary). Neither results from cross-sectional or time lag data can inform organizations or researchers about the simultaneous effects of all three variables. However, I propose that results from repeated cross-sectional data can.

Thus, the purpose of this study is to use the HAPC model to simultaneously examine the influence of age, period, generations, and (if the above simulation supports it) their interactive influence on job satisfaction. Although the HAPC model has been used in a single study in the management literature to analyze job satisfaction data (Kowske et al., 2010), this study did not test for significant differences between the generations, nor did it test time period trends. Moreover, it is also possible that the interaction between time period and generations as well as the interaction between age and generations will affect job satisfaction.

CHAPTER 7

STUDY 2 METHOD

Sample

The General Social Survey (GSS) is a nationally representative, freely available sample that has been collected for most years between 1972 and 2012 (Smith et al., 2015). Although the GSS spans 40 years the same individuals are not measured in each administration, thus the GSS is a repeated cross-sectional dataset. To correct for sampling bias, I used the WTSSALL weight variable to weight all of my analyses. I also removed the Black oversamples collected in 1982 and 1987 as suggested by the GSS developers.

Measure of Job Satisfaction

The GSS includes four measures of overall job satisfaction, however only one item has been consistently asked since 1972 and thus, this item was adopted for the present analysis. The item asks: “On the whole, how satisfied are you with the work you do?” Although assessing a construct with just a single item is not optimal, it is possible to draw correct inferences from a single item (Wanous, Reichers, & Hudy, 1997).

Data Analysis

The data was analyzed using the HAPC model (Yang & Land, 2013) using the R package lme4 (Bates, Maechler, Bolker, & Walker, 2015). Because the HAPC treats age as a fixed effect nested within the crossed random-effects of birth cohort and time period it can estimate the effects of age, time period, and generation. Unlike other applications of the HAPC model I treat birth cohorts as a random factor and generations as a level-two fixed factor. This allows me to test for mean job satisfaction differences among the different generations. Moreover, I also include a time trend variable to test for time period effects on job satisfaction. While the variance components will be estimated they will only be used to determine how much variance the fixed-effects of age, time period, and generation explain.

CHAPTER 8

STUDY 2 RESULTS

Descriptive statistics for the job satisfaction item can be found in Table 7. After removing the oversamples, the Silent generation made up 31% of the sample, the Baby Boomers made up 41%, Generation X made up 25%, and the Millennials made up 3%. The average response to the job satisfaction item was 3.30 across all generations, 3.43 for the Silent generation, 3.26 for the Baby Boomers, 3.23 for Generation X, and 3.13 for the Millennials. The standard deviations were .81 across all generations, .76 for the Silent generation, .83 for the Baby Boomers, .81 for Generation X, and .86 for the Millennials.

The HAPC analyses can be found in Table 8. Using likelihood ratio tests and information criteria, I compared three different models to determine the best fitting one. The null model did not contain any predictors and only estimated the level-1 and level-2 variances. The ICCs for cohort and period were constructed using these variances and found to be .06 and .01, respectively. Although small, in the applied literature ICCs typically range from .05 to .20 (Bliese, 2000). I then tested the null model against the main effects model, which included predictors for the curvilinear effect of age, the period effect, and mean comparisons of the Boomer Generation to each of the other generations. Both the likelihood ratio test and the information criteria supported the main effects model over the null model (Δ Deviance = 413, Δ df = 6).

I then compared the main effects model to the interaction model, which estimated fixed-effects for the generation $\times$ period and generation $\times$ age interactions. Although the likelihood ratio test supported the interaction model over the main effects model, none of the interactions were significant. Further, the Bayesian Information Criterion (BIC) for the main effects model was smaller than the BIC for the interaction model. Because the BIC penalizes model fit for the number of estimated parameters it is likely that the interaction model is over-parameterized. Thus, the results supported the main effects model as the best fitting model.

The main effects model found a significant main age effect (γ_{01}= .01) and quadratic age effect (γ_{02}= <.00). This effect is plotted in Figure 4. Next, the model found a significant and negative period effect (γ_{03}= -.03), which suggests that job satisfaction has been declining since 1972. Finally, the model found that the average reported job satisfaction for both the Silent Generation and Generation X was significantly greater than the average job satisfaction reported by the Boomer Generation (γ_{04}= .06 and γ_{05}= <.00, respectively).

Table 7. Descriptive Statistics by Generation

	Silent Generation	Boomers	Generation X	Millennials	All Generations
Mean	3.43	3.26	3.23	3.13	3.30
SD	.76	.83	.81	.86	.81
N	12568	16735	10271	1042	40616

Note. SD = Standard Deviation; N = Sample Size.

Table 8. HAPC Model Estimates

Model		Fixed Effect Estimate	SE	Variance Components	Estimate	Information Criteria AIC	BIC
Null Model	γ_{00}	3.33*	.03	τ_{00j}	.04	97558.33	97592.78
				τ_{00k}	.01		
				σ^2	.63		
Main Effects Model	γ_{00}	2.65**	.14	τ_{00j}	<.00	97156.47	97242.59
	γ_{01},Age	.01**	.00	τ_{00k}	<.00		
	γ_{02},Age Squared	<.00**	.00	σ^2	.63		
	γ_{03},Period	-.03**	.01				
	γ_{04},Silent	.06**	.02				
	γ_{05},X	< .00**	.00				
	γ_{06},Millennial	-.04	.03				
Interaction Model	γ_{00}	2.70**	.15	τ_{00j}	<.00	97150.46	97288.25
	γ_{01},Age	.01**	.00	τ_{00k}	<.00		
	γ_{02},Age Squared	<.00**	.00	σ^2	.63		
	γ_{03},Period	-.03**	.01				
	γ_{04},Silent	.06**	.02				
	γ_{05},X	<.00**	.00				
	γ_{06},Millennial	.06	.30				
	γ_{07},Period x Silent	<.00	.00				
	γ_{08},Period x X	<.00	.00				
	γ_{09},Period x Millennial	<.00	.01				
	γ_{010},Age x Silent	<.00	.00				
	γ_{011},Age x X	<.00	.00				
	γ_{012},Age x Millennial	<.00	.01				

Note. **p* < .05; ***p* < .01; SE = Standard Error; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion.

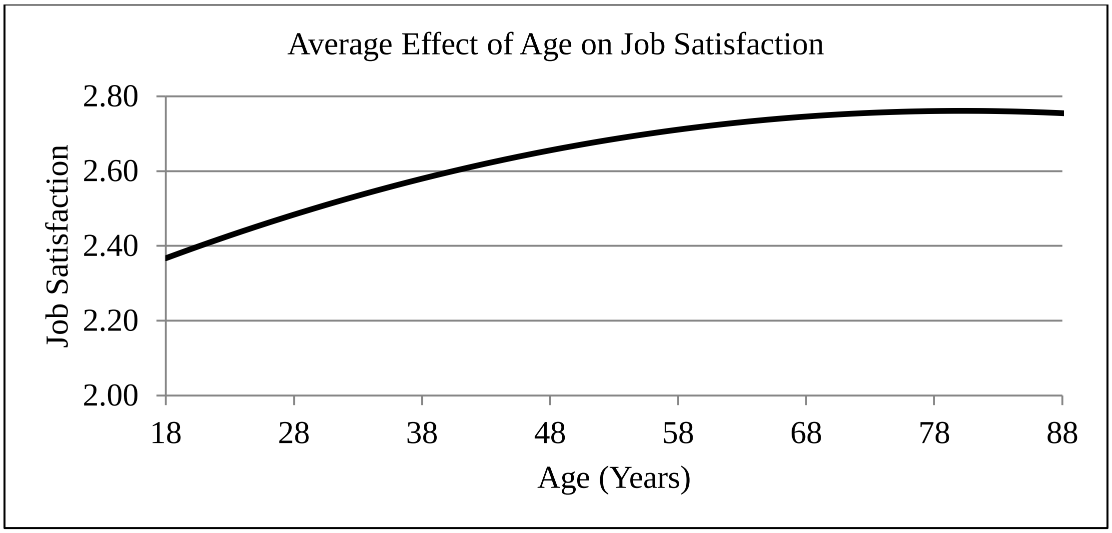

Figure 4. Predicted Effect of Age on Job Satisfaction Averaged Across All Generations

CHAPTER 9

STUDY 2 DISCUSSION

Overall, the results from the HAPC model suggest that age, period, and generations all significantly affect an employee's job satisfaction. The age effect shows that job satisfaction increases towards a maximum as an employee ages. The period effect provides evidence that job satisfaction has been declining since the early 1970s. The generation effects provide evidence that compared to the Boomer generation members of the Silent Generation and Generation X are more satisfied with their job, on average, and members of the Millennial Generation are as satisfied with their job, on average. Because this is the first time each of these effects has been estimated and tested at the same time, it is important to discuss how these results compare to previously reported results.

The form of the relationship between age and job satisfaction has received mixed support. Several primary studies have found a nonlinear relationship between age and job satisfaction (Clark, Oswald, & Warr, 1996; Hochwarter, Ferris, & Perrewé, 2001; Kacmar & Ferris, 1989; Zacher, Jimmieson, & Bordia, 2014). Specifically, these studies found an initial decrease in job satisfaction after employees entered the workforce, followed by a later increase as they progressed through their careers. In contrast, a recent meta-analysis found a small, positive linear relationship between age and job satisfaction and did not find evidence of a nonlinear relationship (Ng & Feldman, 2010). In comparison, the HAPC model results from this study found a different nonlinear age-job satisfaction relationship that shows a monotonically increasing relationship that slows down and begins to level off for older employees (see Figure

4). Because generational effects were not controlled for in either the primary studies (Clark et al., 1996; Hochwater et al., 2001; Kacmar & Ferris, 1989; Zacher et al., 2014) or the meta-analysis (Ng & Feldman, 2010), it is possible that the relationship was misestimated. Indeed, the generational comparisons estimated by the HAPC model show that, on average, members of the Silent Generation and Generation X had higher job satisfaction scores then members of the Baby Boomers. In cross-sectional data, this relationship could manifest as a curvilinear age effect, where both younger and older employees provide higher ratings of job satisfaction than middle-age employees, which is what has typically been found in primary studies (Clark et al., 1996; Hochwater et al., 2001; Kacmar & Ferris, 1989; Zacher et al., 2014).

Similarly, the finding that time period negatively and significantly affected job satisfaction is important because past studies examining this effect have yielded mixed results (Bowling et al., 2013; Kalleberg, 2013; Smith et al., 1976). That is, using three large repeated cross-sectional datasets, Bowling et al. (2013) found that average levels of employee job satisfaction have remained relatively stable across time, whereas Smith et al. (1976) found a decrease in average job satisfaction across time. However, the studies conducted by Bowling et al. (2013) and Smith et al. (1976) did not control for generational differences. Kalleberg (2013) found an average decrease in job satisfaction across time, but the relationship became positive after a cohort variable was included. It is possible that these three studies have all come to different conclusions because they have not controlled for age and generation effects. The strong inter-correlation among these variables could result in unstable estimates when all effects are present, but not controlled for (Bell & Jones, 2014).

Finally, the HAPC results suggest that job satisfaction does differ, albeit weakly, across generations. That is, job satisfaction dropped from the Silent Generation to the Baby Boomer generation then seemed to rise slightly from the Baby Boomer generation to Generation X, only to drop back down for the Millennial generation. This is evidenced by the positive and significant mean difference between the Silent and Baby Boomer generations, the positive and significant mean difference between Generation X and the Baby Boomer generation, and the non-significant, but negative mean difference between the Millennial and Baby Boomer generations. This finding largely agrees with the HAPC results provided by Kowske et al. (2010). They used a repeated cross-sectional dataset to examine the effects of age, period, and generation on job satisfaction. Based on a plot of the cohort random-effects they concluded that overall job satisfaction decreased from the Silent Generation to the Boomer Generation and then increased from the Boomer Generation to the Millennial Generation. A meta-analysis of cross-sectional data, however, found different results (Costanza et al., 2012). Specifically, the meta-analysis found that previous generations are more satisfied with their jobs than subsequent generations. But, the only significant difference was between Generation X and the Millennial Generation (Costanza et al., 2012). It is possible that the meta-analytic results differ from the HAPC results because the meta-analysis was conducted on cross-sectional results and could not control for age effects.

CHAPTER 10

GENERAL DISCUSSION

The purposes of studies 1 and 2 were to assess the extent of bias present in generational inferences estimated from cross-sectional data and provide an example of the application of the HAPC model to actual data. In doing so, these studies provided three important findings. First, the simulation study found that mean generational comparisons estimated from cross-sectional data were generally inaccurate. Second, the simulation study showed that the HAPC model can and should be used to accurately estimate generational fixed-effects, period fixed-effects, age fixed-effects, and their interactions. Third, the results of the second study found that age, period, and generation effects estimated from repeated cross-sectional data can still differ from cross-sectional and longitudinal estimates of those effects even in the absence of generational interactions.

It is not uncommon for organizational studies to list their use of a cross-sectional design as a limitation when attempting to examine period and generational-based changes (Becton et al., 2014; Cenamo & Gardner, 2008; Costanza et al., 2012; D'Amato & Herzfeldt, 2008; Hess & Jepsen, 2009; Sullivan, Forret, Carraher, & Mainiero, 2009; Westerman & Yamamura, 2007). For example, in their limitations section Costanza et al. (2012) stated, "…most research on generational differences and almost all research focused on work-related outcomes have employed cross-sectional designs. As has been discussed by previous research…there are numerous limitations to cross-sectional research when studying generational differences, particularly the inability to separate variance attributable to generational, age, and period effects"

(Costanza et al., 2012, p. 389). In agreement, the results of Study 1 showed that under most circumstances it is not possible for cross-sectional research to separate generation and age effects while holding period effects constant. When the dependent variable under investigation is influenced by an interaction between either generations and age or generations and period then the results of cross-sectional designs will not converge with the results of repeated cross-sectional designs. But, if both of these interactions are absent, cross-sectional designs can provide accurate estimates of generational differences controlling for the age and period effects. Thus, it is important for organizational research on generational differences to determine which organizational variables are impacted by these interactions.

To date, no research has investigated such effects. Indeed, with the exception of Becton et al. (2014), organizational research has not even theorized about the presence of generational and age and/or generational and period interactions. Because of this lack of theoretical guidance, future generational research may have to proceed in an exploratory manner to determine the presence of these effects. One such way is to estimate these interaction effects along with their main effects using the HAPC model. Study 1 showed that it is possible to use the HAPC model to simultaneously estimate fixed effects for age, generations, period, generation $\times$ age interactions, and generation $\times$ period interactions as well as the cohort and period random effects. Moreover, the HAPC model is able to estimate the period, age, and interaction fixed effects with greater accuracy than the generational fixed effects. However, if the data do not allow to first test for these interactions, researchers are strongly cautioned to avoid drawing inferences as to the nature of generation and period effects.

It is also important to note that in order to test the interaction effects, the main effects must also be included (Cohen, Cohen, West, & Aiken, 2003). Previous treatments of the HAPC model have not directly estimated and tested these effects (Kowske et al., 2010; Yang & Land, 2006; 2008). Instead, they have tested the significance of the period and cohort (or generational) variance components. Following this, they have then plotted the random period and cohort effects and investigated the plots for trends (Kowske et al., 2010; Yang & Land, 2006; 2008). While random-effects plots are useful aides in the model building process, they should not be used to infer the presence or absence of generational and period effects. To test for the presence of these effects, researchers should include categorical variables for the generations and a time variable for the period.

Indeed, failing to directly estimate and control for these effects could result in an omitted variable bias (Meade, Behrend, & Lance, 2009). This bias could explain why the effects of age, period, and generation on job satisfaction reported in this study differ from previous studies even though no generational interactions were found by the HAPC model. Specifically, because age, period, and generation effects are related to each other and impact job satisfaction, it is necessary to model all three effects to obtain unbiased estimates of each effect (James, Mulaik, & Brett, 1982; Meade et al., 2009). For cross-sectional studies examining the impact of age on job satisfaction, it is still necessary to control for generational effects by including generational categorical variables. For time series studies that investigate change in job satisfaction across time, it is still necessary to control for age and generational effects, which might be possible by including the average respondent age for each time period (Kalleberg, 2013).

Future Research and Limitations

It is important for future research to investigate age, period, and generation effects using the HAPC model. These results can then be compared to those of previous studies. It is possible that the generational inferences drawn for previous cross-sectional studies are wrong. These inferences could be wrong because they were either affected by a generational interaction or they were estimated without controlling for age and period effects. Future research, however, needs to investigate the impact of modeling one of the APC effects without controlling for the others.

Beyond methodological issues, future research also needs to address the validity of the generational typology used by generational studies. That is, most, if not all, generational studies apply generational labels to employees based off of the generational typology forwarded by Strauss and Howe (1991). As there is no empirical basis for this typology, future research needs to determine a more defensible way to measure generations (Dencker et al., 2008). One possible way to do this is to draw from the literature on organizational faultlines and use latent class analysis to identify generational subgroups (Lawrence & Zyphur, 2011). Moreover, future research needs to begin to investigate the extent to which intra-generational differences affect organizational variables and how these effects compare to inter-generational differences (Twenge, 2010).

Both studies have several limitations that could hurt their generalizability, but could also serve as foci for future research. Similar to other simulation studies, Study 1 only examined a subset of possible simulation factors and levels. Future research needs to investigate a) the impact that misspecifying the generation year cut-offs has on generational difference estimates obtained from both repeated cross-sectional and cross-sectional designs, b) the extent to which unbalanced generational groups affects generational comparisons, and c) how accurate the HAPC model estimates are at lower level-1 and level-2 sample sizes. Moreover, Study 1 only examined how the presence of higher-order effects impacted cross-sectional designs, it would also be helpful to know if and how they impacted time-lag designs.

Study 2 also suffered several limitations. First, only a single a job satisfaction item was measured across all data collection waves. Although single item measures of job satisfaction have been found to be reliable (Wanous et al., 1997), nonetheless, a multiple item measure of job satisfaction would have been more preferable. Second, although the GSS covers a large span of years (1972 – 2012), members of the silent generation were no younger than 30 and members of the Millennial generation were no older than 30. Third, even though data was collected across various time periods, repeated cross-sectional designs do not allow researchers address causality.

Conclusion

It is important for researchers and practitioners alike to recognize the pitfalls of drawing generational inferences from cross-sectional data. This paper showed that such inferences can be biased by the presence of generational interactions. Furthermore, the absence of these interactions does not ensure that inferences made from cross-sectional data will agree with those made from repeated cross-sectional data. Thus, out of both theoretical and practical necessity, organizational researchers should estimate and test generational inferences from repeated cross-sectional data using the HAPC model.

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