Approaches for Performing Age-Adjustment in Trend Analysis

Xianfen Li[1] and Mary Ann Bush[1]
[1]National Center for Health Statistics, 3311 Toledo Rd, Hyattsville, Maryland, 20782

Abstract
The National Center for Health Statistics (NCHS) produces publications on a wide range of health indicators from its survey data systems. Many of these reports present analyses of trends over time. Age-adjustment is used to minimize differences in observed estimates that result from changes to the age structure in a population over time. In NCHS trend analyses, age-adjusted estimates are calculated using the age distribution for the year 2000 U.S. standard population. This paper will describe two linear regression trending approaches involving age-adjusted estimates. One approach is the adjustment of the survey sample weights to reflect age-adjustment. The other approach uses age as a covariate in a regression model. The two approaches are compared to provide NCHS survey data users with options for their trend analysis work.

Key Words: trend analysis, survey, age-adjustment, 2000 U.S. standard population, linear regression

1. Introduction

The National Center for Health Statistics produces numerous publications on a wide range of health indicators every year from its survey data systems or administrative data systems. Many of these reports analyze trends over time, such as *Health, United States*, which presents an annual overview of national trends in health statistics submitted by the Secretary of the U.S. Department of Health and Human Services to the President and the U.S. Congress (HUS, 2017). However, the age structure of the study population may change over time. When the health indicator is related to age, changes in the underlying age structure may confound any differences observed in the indicator over time, and the conclusions drawn from the trend analysis may be affected. Therefore, minimizing the effect of the changing age structure is necessary for valid analyses. Age-adjustment is the technique used to adjust for the changing age structure in study populations by calibrating to a standard population so that all of the time periods' populations have same age structure as the standard population. This paper will focus on age-adjustment during trend analysis of survey data.

Disclaimer: The findings and conclusions in this report are those of the authors and do not necessarily represent the official position of the Centers for Disease Control and Prevention.

Direct age adjustment is used in descriptive procedures in SUDAAN, which allows for the correct analysis of complex sample survey data. The equation for direct age adjustment is:

$$P_{adj} = \sum_{i=1}^{n} p_i * (w_i/W) \tag{1}$$

$p_i =$ prevalence estimate in age group i in the study population
$w_i =$ standard population in age group i
$n =$ total number of age groups over the age range of the age-adjusted estimate

$$W = \sum_{i=1}^{n} w_i$$

The standard population can be obtained from an external source, such as the Census 2000 projected U.S. population, or from the population represented by the entire sample that the analyst is using. NCHS uses direct age adjustment for descriptive analyses using the Census 2000 projected U.S. population as the standard population (Klein and Schoenborn, 2001) in many of its publications. However, for trend analyses of survey data, SUDAAN has no available technique to incorporate direct age adjustment to an external source in commonly used inference procedures such as PROC REGRESS. Published in 2018, the *National Center for Health Statistics Guidelines for Analysis of Trends* recommends age adjustment of survey sample weights for trend analysis of age-adjusted survey data (Ingram, et al., 2018). In addition, some NCHS data users and analysts use age as a covariate in regression models to adjust trend analyses. To provide NCHS survey data users with options for trend analysis, this paper describes the age-adjusted survey sample weights approach in detail, and compares it with the approach using regression-based covariate adjustment.

2. Trend Analyses of NCHS Survey Data

The *National Center for Health Statistics Guidelines for Analysis of Trends* provides general guidelines for trend analysis. For survey data, the report recommends trend analysis using three steps:

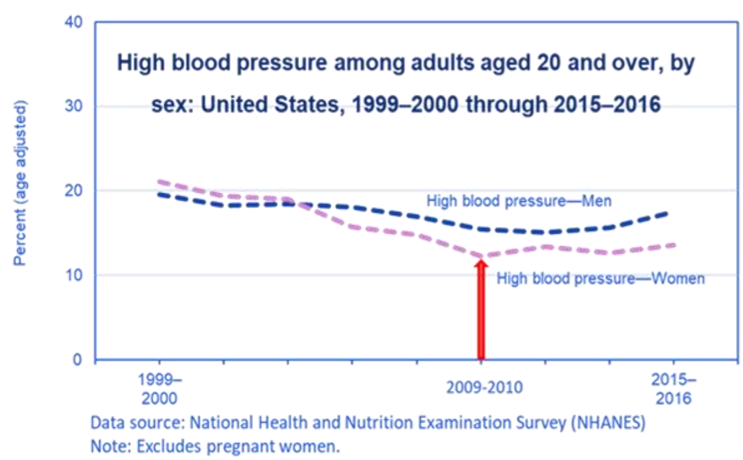
1) Assess trend for nonlinearity: Use record-level data and survey analysis software to fit trend models to incorporate the survey design and sample weights, adjust for year-to-year correlation, and calculate degrees of freedom. Polynomial regression models, orthogonal polynomial contrasts, and restricted cubic spline regression models can be used.
2) Identify the location and number of change points (joinpoints): If nonlinearity in the trend is detected in step 1, use aggregated data, such as those calculated from SUDAAN's proc descript procedure, and National Cancer Institute's (NCI) JoinPoint software to find the joinpoints, where segments are connected and the changes in trend occur. One important caveat is that JoinPoint software cannot incorporate the survey sample design in the analysis.
3) Obtain the final results: If joinpoints are identified in step 2, use record-level data and survey software to fit piecewise regression models to obtain the final slope estimates and perform tests of hypotheses, which reflect the survey sample design.

Polynomial regression models are generally applied in NCHS publications that include trend analyses, such as in *Health, United States*, in Step 1. The aggregated data in step 2 are direct age-adjusted point estimates and standard error estimates, which are produced by SUDAAN for most NCHS reports and directly age-adjusted to the 2000 U.S. standard population, if analyst is analyzing age-adjusted trend. However, SUDAAN cannot incorporate the direct age adjustment to an external source in regression procedures. To make the analysis consistent across the three steps (i.e. every step is age-adjusted to 2000 U.S. standard population), the *National Center for Health Statistics Guidelines for Analysis of Trends* recommends adjusting the sample weights to reflect the age adjustment when assessing age-adjusted trends. A more detailed description for this approach follows in section 3.

3. Age-Adjusted Survey Sample Weights Approach

Age-adjusted survey sample weights essentially function as poststratification weights. Poststratification is an adjustment of the sample weights of responding units so that the totals over various demographic categories match known population totals (Korn and Graubard, 1999 a).

Figure 1. High blood pressure among US adults aged 20 and over by sex.



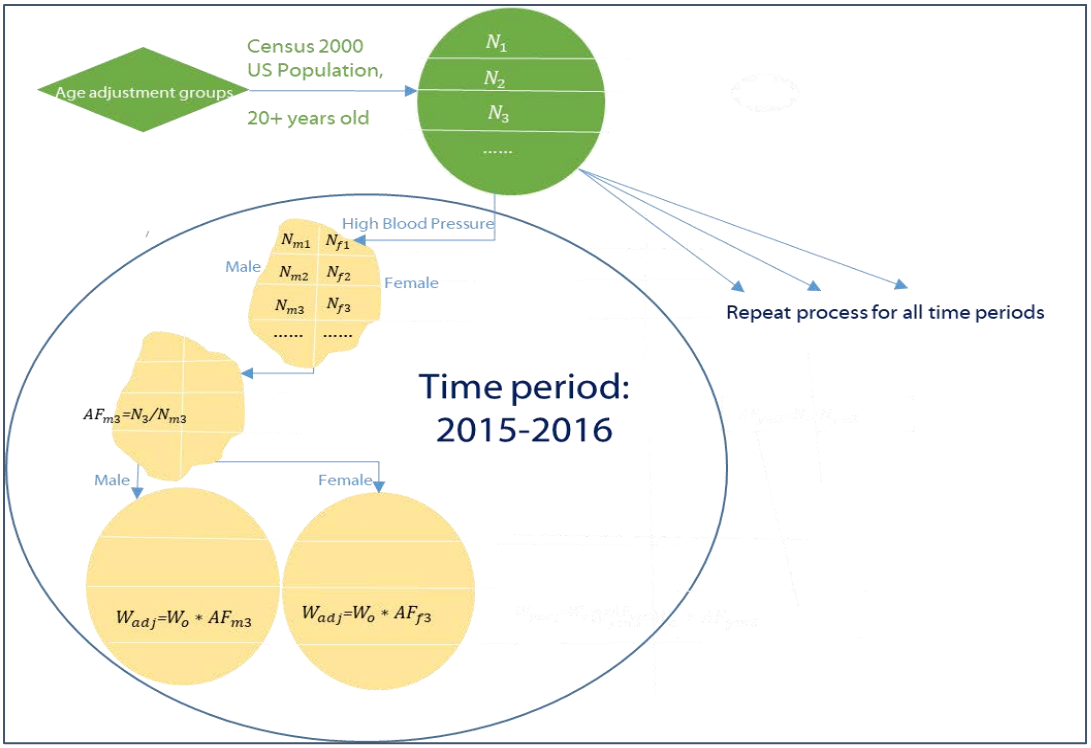
When the age-adjusted survey sample weights approach is used, the analyst should proceed in two steps: (1) Adjust each respondent's original sample weight to make the study population have the same age structure as the 2000 standard population; and (2) Follow the three steps in Section 2 above to analyze survey data, using the age-adjusted sample weight for polynomial regression (step 1 above) and piecewise regression (step 3 above). The aggregated data (step 2 above), which are age-adjusted to 2000 standard population and produced with the original sample weights (not the age-adjusted sample weights) in the SUDAAN descriptive procedure, are then used as input into JoinPoint software.

To adjust the original sample weights to the age structure of the 2000 standard population (Ingram, et al., 2018):

1) Produce an "estimated" population count in the study population by summing the sample weights of the records in each of the age categories that were used to compute the age-adjusted rates.

2) For each age category, calculate an adjustment factor by dividing the "standard" population count (from the 2000 U.S. standard population) by the corresponding estimated population count.

Figure 2: Flowchart for age adjustment of the survey sample weights of trend lines.



3) Compute an "adjusted" sample weight by multiplying the record's original sample weight by the adjustment factor.

This three-step process needs be conducted in each of the age categories used to compute the age-adjusted rates for each time period of the trend line for each population subgroup the analyst is examining. Figure 1 presents trends in high blood pressure (HBP) among U.S. adults aged 20 and over from the time period 1999-2000 through 2015-2016 for males and females. The prevalence estimates in Figure 1 are directly age-adjusted to 2000 standard population and produced by SUDAAN from NCHS' National Health and Nutrition Examination Survey (NHANES). High blood pressure is defined as having measured HBP (systolic pressure ≥ 140 mm Hg or diastolic pressure ≥ 90 mm Hg), regardless of medication use. Pregnant subjects are excluded from analysis. The flowchart in Figure 2 illustrates the entire procedure of age-adjusting survey sample weights for the trend lines in Figure 1.

At the beginning of the process of age adjustment of survey sample weights (Figure 2), the analyst needs to choose the appropriate age adjustment groups for the studied health indicator. In the example of HBP (Figure 1), five age groups were used: 20-34, 35-44, 45-54, 55-64, and 65 years and over. Next, the 2000 U.S. standard population totals for each of the age adjustment groups are calculated, which are shown as N_1-N_5 in Figure 2.

For the study population in 2015-2016, the age-adjusted survey sample weights are calculated as follows:

1) For males and females, respectively: Compute the estimated population count by summing the sample weights of the records used in calculating the prevalence within each of the five age-adjustment groups, producing N_{m1}-N_{m5} for males and N_{f1}-N_{f5} for females.
2) For each-age adjustment group, compute an adjustment factor by dividing the standard population count (from the 2000 U.S. standard population) by the corresponding estimated population count: for example, for males in age group 3, divide the standard population total (N_3) by the sum of sample weights (N_{m3}) to get the adjustment factor AF_{m3} .
3) For each record used in the prevalence estimating for males in age group 3, compute the adjusted sample weight by multiplying the record's original weight by the adjustment factor as W_{adj}=$W_o * AF_{m3}$.
4) Repeat step 3 for each age group for males and females to create the age-adjusted survey sample weights for each record used in calculating the prevalence. The new weights ensure that both males and females have the same age structure as the 2000 U.S. standard population for those aged 20 years and over.

In NHANES 2015-2016, males and females have different age structures, which are different from the 2000 standard population, so age adjustment of sample weights needs to be applied to males and females separately. Table 1 shows the selected calculations from the adjustment process for HBP for 2015-2016. The estimated population total from records used in the prevalence estimating is different from 2000 U.S. standard population for each age group, and the magnitude of difference varies across the five age groups. Overall, males and females have similar estimated population trends as suggested by the estimated population total across five age groups, but the estimated population in each age group varies between males and females.

Table 1: Age-adjustment factors for high blood pressure of 2015-2016 for five age groups by sex.

		High Blood Pressure (2015-2016)					
Total		**Total**		**Male**		**Female**	
Age Adjustment Groups	**2000 Standard Population**	Estimated Population	Adjustment Factor	Estimated Population	Adjustment Factor	Estimated Population	Adjustment Factor
20-34 years	55,490,662	60,592,517	0.9158	31,657,114	1.7529	28,935,403	1.9177
35-44 years	44,659,185	37,112,502	1.2033	17,995,209	2.4817	19,117,293	2.3361
45-54 years	37,030,152	42,881,385	0.8635	21,284,311	1.7398	21,597,074	1.7146
55-64 years	23,961,506	38,147,170	0.6281	18,799,647	1.2746	19,347,523	1.2385
65+ years	34,709,480	46,852,996	0.7408	20,343,300	1.7062	26,509,696	1.3093

Repeat the process for 2015-2016 for all the other time periods, so that all the time periods have the same age structure for males and females, respectively, after the adjustment. Then the analyst can move to step 2 of the age-adjusted survey sample weights approach: use the age-adjusted survey sample weights to do the regression in step 1 (polynomial regression for assessing nonlinearity), detect joinpoints in JoinPoint software in step 2 (aggregated data produced with the original sample weights), and use the age-adjusted survey sample weights to do the regression in step 3 (piecewise regression for final results if joinpoint(s) are identified by JoinPoint software). The age-adjusted weights are only used for regression, because the point estimates and standard errors of prevalence (aggregated data) presented in reports need to be produced from SUDAAN's descriptive procedures, by direct age adjustment to 2000 standard population and using the original weights. The two kinds of weights will produce the same point estimates for prevalence, but the standard errors may differ. Table 2 shows the difference in standard errors for the trend lines in Figure 1.

Table 2: Age-adjusted high blood pressure estimates from original weights (age standardized to 2000 standard population using direct method) and age-adjusted weights.

Time	**Male**				**Female**			
	Original Weights		**Age-adjusted Weights**		**Original Weights**		**Age-adjusted Weights**	
	Percent	SE	Percent	SE	Percent	SE	Percent	SE
1999-2000	19.6	1.8	19.6	1.7	21.1	1.1	21.1	1.4
2001-2002	18.3	0.9	18.3	0.9	19.4	0.8	19.4	1.0
2003-2004	18.4	1.6	18.4	1.7	19.0	0.9	19.0	1.0
2005-2006	18.1	1.2	18.1	1.1	15.7	0.7	15.7	0.8
2007-2008	16.9	0.8	16.9	0.6	14.8	0.5	14.8	0.6
2009-2010	15.4	0.6	15.4	0.6	12.3	0.8	12.3	0.7
2011-2012	15.1	0.8	15.1	0.9	13.4	1.1	13.4	1.0
2013-2014	15.6	1.3	15.6	1.3	12.6	0.8	12.6	0.8
2015-2016	17.5	1.2	17.5	1.2	13.6	0.9	13.6	0.9

4. Covariate Adjustment Approach

Covariate adjustment means including variables other than main predictor in a regression model. Covariates may be effect modifiers, confounders, or precision variables. This approach is used broadly in inferential analysis to adjust for multiple factors at the same time. This technique is also used to perform age adjustment for trend analyses of survey data in step 1 and step 3 of Section 2. For example, in step 1, polynomial regression can be used to assess for nonlinearity using the formula as below:

$$g(\theta|X_i, W_i) = \beta_0 + \beta_1 X_i + \beta_2 Z_i + \beta_3 X_i^2 + \beta_4 X_i^3 + \varepsilon_i \qquad (2)$$

$X -$ time period, continuous variable

$Z -$ age adjustment group, categorical variable

The formula in (2) can be used to detect cubic trends. If only quadratic trends need to be detected, the highest order term in (2) will be $\beta_3 X_i^2$. Generally, the higher order terms for time should be limited to quadratic or cubic (Ingram, et al., 2018).

The covariate adjustment approach includes the age adjustment variable in the model to assess effect modification. The aggregated data in step 2 of Section 2 are age-adjusted to the 2000 standard population and produced with the original sample weights in the SUDAAN descriptive procedure. The original survey sample weights are used for each of the three steps in Section 2.

5. Example of the Two Age-Adjustment Approaches

In this section, the trend lines in Figure 1 will be used to demonstrate two trend analysis approaches. The first, the age-adjusted survey sample weights approach, includes a time variable (polynomial regression) or segment variable (piecewise regression), and age-adjusted weights are used. The second, the covariate adjustment approach, includes the age as a covariate in the model as well as the time variable/segment variable, and original weights are used. Table 3 presents the results for nonlinearity assessment from these two approaches.

Table 3: Results for assessing nonlinearity from age-adjusted survey sample weights approach and covariate adjustment approach

			Age-Adjusted Survey Sample Weights				**Covariate Adjustment**			
Trend Line	**Model**	**Independent Variables and Effects**	*Beta Coeff.*	*SE Beta*	*T-Test B=0*	*p-value T-Test B=0*	*Beta Coeff.*	*SE Beta*	*T-Test B=0*	*p-value T-Test B=0*
Male HBP	**1**	Quadratic	0.0273	0.0177	1.5415	0.1255	0.0226	0.0178	1.2688	0.2066
	2	Linear	-0.2152	0.0865	-2.4886	0.0140	-0.1974	0.0867	-2.2772	0.0243
Female HBP	**1**	Quadratic	0.0444	0.0144	3.0941	0.0024	0.0437	0.0135	3.2516	0.0014

The trend lines in Figure 1 have nine time periods. According to the *National Center for Health Statistics Guidelines for Analysis of Trends*, 7-11 time points are needed for detecting a quadratic trend (JoinPoint Help Manual, 2017). Therefore, a quadratic regression model was fit separately for males and females at the beginning in SUDAAN. For Model 1 among males, both approaches indicate that there is no quadratic trend for HBP. By contrast, Model 2 (reduced model) results indicate that a significant decreasing linear trend is present for HBP prevalence among males for both approaches. For HBP among females, both approaches lead to the conclusion that a quadratic trend exists. There is no need to rerun the reduced model to assess for a linear trend for females.

Because nonlinearity is detected in the trend for females, aggregated estimates (using the original weights and directly age-adjusted to 2000 standard population) of the female trend line are input into NCI's JoinPoint software to search for possible joinpoints. JoinPoint software identifies one joinpoint at 2009-2010 indicated by the red arrow in Figure 1.

Because a joinpoint is identified, piecewise regression analysis is conducted in SUDAAN to obtain the final results (Table 4). The two age-adjustment approaches reach the same conclusion: HBP prevalence among females decreased from 1999-2000 to 2009-2010 but was stable from 2009-2010 to 2015-2016.

Table 4: Results for piecewise regression from age-adjusted survey sample weights approach and covariate adjustment approach for females.

	Age-Adjusted Survey Sample Weights				**Covariate Adjustment**			
Piecewise Regression	*Beta Coeff.*	*SE Beta*	*T-Test B=0*	*p-value T-Test B=0*	*Beta Coeff.*	*SE Beta*	*T-Test B=0*	*p-value T-Test B=0*
Segment1	-0.8637	0.1191	-7.2529	<0.0001	-0.9118	0.1092	-8.3462	<0.0001
Segment2	0.1028	0.1651	0.6224	0.5347	0.0569	0.1772	0.3212	0.7485
Contrast	*DF*	*p-value S_waite Adj F*	*p-value S_waite ChiSq*	*p-value Wald F*	*DF*	*p-value S_waite Adj F*	*p-value S_waite ChiSq*	*p-value Wald F*
Change in slope	1	0.0002	0.0001	0.0002	1	0.0002	0.0001	0.0002

6. Discussion

This report reviewed two different approaches for age adjustment in trend analysis of complex survey sample data. The age-adjusted survey sample weights approach adjusts the original survey sample weights by directly standardizing the study population at each time period to an external standard population. This approach can be labor-intensive, as adjustment factors must be calculated for each subgroup (here, sex), each of the five age groups, and each of the nine time periods.

The covariate adjustment approach does not use information from an external source, but instead, the population represented by the entire sample used in the modeling from all time periods is used as the standard population. For example, in Section 5 a model is fitted to males and females respectively. The standard population used for males is the male population represented by the entire sample used in modeling the male trend from all time periods; the same approach was used for females. Males and females therefore use different standard population. This approach uses the same adjustment factor (coefficients of age dummy variables) in a model (for males and females respectively) for each of the nine time periods.

The age-adjusted survey sample weights approach is closer to direct age adjustment (direct standardization to an external source). For the covariate adjustment approach, the NCHS trend guidelines mention that analysts can also produce predictive margins (Korn and Graubard, 1999 b) from the model described in step 1 of Section 2 and as aggregated data for step 2 in Section 2. The predictive margins from the covariate adjustment approach can be the exact same as those from direct age standardization to population represented by the entire analytic sample (i.e. the sum of the analytic sample weights). This is, because predictive margins are a generalization of the direct standardization approach (i.e. directly standardized to the population represented by the entire analytic sample) and equivalent when an appropriate model is used (Witt and Spagnola, 2009). The three steps in Section 2 for the covariate adjustment approach are therefore more consistent with each other, because each step adjusts to the same population. However, aggregated data from the covariate adjustment model could lead to conclusions on the number or location of joinpoints (step 2, Section 2) that are different from those resulting from the analysis standardized to the 2000 standard population.

The age-adjusted survey sample weights approximates but is not equivalent to the direct age adjustment method (age adjustment to external source). If age-adjusted weights are used to calculate prevalence estimates and standard errors for each time period, the point estimates from direct age adjustment (age adjustment to external source, and using original weights) and age-adjusted weights are the same but standard errors may be different. The age-adjusted weights are only used for regression. The point estimates and standard errors of prevalence estimates presented in reports for each time period should be produced by direct age adjustment (age adjustment to external source, and using original weights) from SUDAAN's descriptive procedures.

The age-adjusted survey sample weights approach has an obvious disadvantage in that it requires a new set of weights for each trend line and may be inconvenient to implement. The covariate adjustment model uses the original survey weights and is relatively easy to implement.

In the current example focusing on HBP, both approaches produced similar findings for the initial assessment of nonlinearity. When nonlinearity was detected and a joinpoint was identified, the subsequent piecewise regression for both approaches produced similar findings for the final slope estimates and tests of trends.

As with most assessments that rely on p-values to assess significance, when p-values for coefficients are close to 0.05 (or other level of significance), the two approaches may lead to different conclusions. For this reason, analysts should be clear about the age-adjustment approach used in their work, and consider reporting p values – not just their conclusions – especially when the p value is close to the level of significance used. Multiple analytic approaches provide analysts with enhanced flexibility to perform trend analysis of complex survey data.

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