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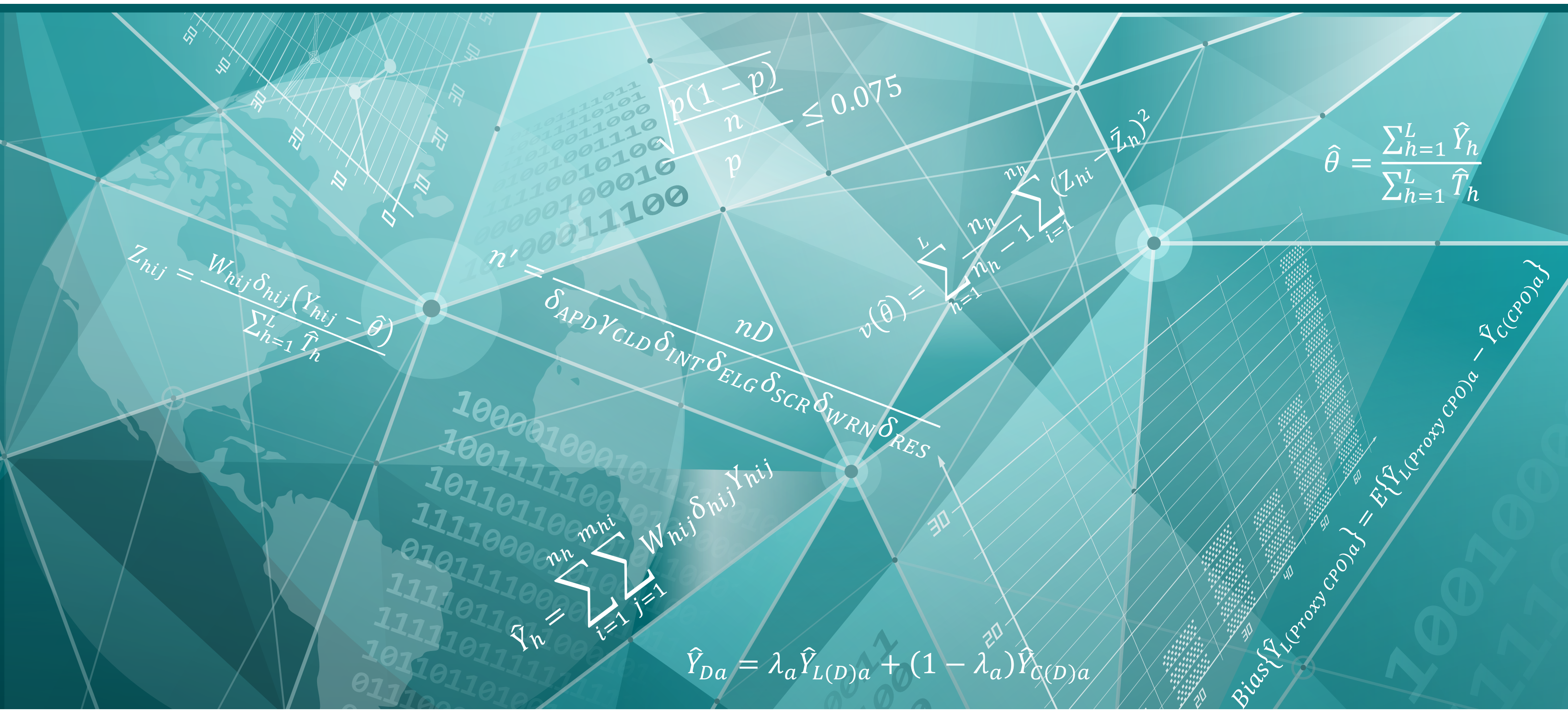

Comparing Results Between Survey Analysis Software and the National Cancer Institute Joinpoint Regression Software for Trend Analyses of Survey Data

Data Evaluation and Methods Research

U.S. CENTERS FOR DISEASE CONTROL AND PREVENTION

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Comparing Results Between Survey Analysis Software and the National Cancer Institute Joinpoint Regression Software for Trend Analyses of Survey Data

Data Evaluation and Methods Research

U.S. DEPARTMENT OF HEALTH AND HUMAN SERVICES
Centers for Disease Control and Prevention
National Center for Health Statistics

Hyattsville, Maryland
September 2025

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Comparing Results Between Survey Analysis Software and the National Cancer Institute Joinpoint Regression Software for Trend Analyses of Survey Data

by Jennifer Rammon, M.S., Kate Hubbard, M.S., Makram Talih, Ph.D., Deanna Kruszon-Moran, M.S., Robin A. Cohen, Ph.D., and Katherine E. Irimata, Ph.D.

Abstract

Objective

This report compares results between survey analysis software and the National Cancer Institute Joinpoint Regression Software for trend analysis of survey data. The "National Center for Health Statistics Guidelines for Analysis of Trends" recommends that analysts use record-level data and survey analysis software to fit desired trend models of survey data. When changes in a trend will be assessed using piecewise regression models, the guidelines recommend that analysts use the most recent version of the Joinpoint software with aggregated data to identify the number and location of joinpoints, then survey analysis software with record-level data to obtain final slope estimates and to conduct tests of hypothesis for the model identified by the Joinpoint software. In practice, the Joinpoint software sometimes produces results that appear incongruent with those generated by the survey analysis software. The purpose of this report is to provide guidance for conducting trend analyses on NCHS survey data to handle and explain these apparent inconsistencies. This report should be considered a supplement to the "National Center for Health Statistics Guidelines for Analysis of Trends."

Methods

Cases were identified where apparent inconsistencies between the Joinpoint software and survey analysis software could occur. Plausible explanations for the apparent differences are discussed through text, examples, and frequently asked questions. Solutions are not provided; rather, recommendations, cautions, and additional information are provided to assist analysts in making the best decisions for their analysis and data.

Results

Most frequently, inconsistencies occur when the prespecified piecewise regression model provided by the Joinpoint software is estimated using survey analysis software and successive slopes are not statistically significantly different from one another, resulting in one or more joinpoints being removed from the final model. Potential explanations are divided into five main categories.

Keywords: time series • piecewise regression • segmented regression • variance-covariance matrix • National Health Interview Survey • National Health and Nutrition Examination Survey

Introduction

"National Center for Health Statistics Guidelines for Analysis of Trends" (1) generally recommends the use of record-level data and survey analysis software (such as SUDAAN, the R survey package, STATA, or SAS/STAT survey procedures) when fitting trend models of survey data. However, when trends are assessed using joinpoint (that is, piecewise, segmented, or broken stick) regression models, the guidelines recommend that analysts use the most recent version of the National Cancer Institute (NCI) Joinpoint Regression Software with aggregated data to identify the number and location of joinpoints, but that survey analysis software with record-level data be used to obtain final slope estimates and to conduct tests of hypothesis for the model identified by the Joinpoint software.

In practice, some analysts have observed conflicting results between the Joinpoint software and survey analysis software. Specifically, sometimes differences in statistical significance exist between polynomial regression (survey analysis software), polynomial contrasts (survey analysis software), and piecewise regression (Joinpoint software and survey analysis software). Other times, differences exist between the number of joinpoints identified by the

Joinpoint software and the number of joinpoints estimated to be statistically significant by the survey analysis software in the prespecified segmented regression model. For example, the Joinpoint software may identify two joinpoints in a trendline, while the survey analysis software only estimates that one is statistically significant. This could happen because the Joinpoint software performs aggregate-level analysis and the survey analysis software performs record-level analysis. However, it could also be due to other reasons. Easily identifying the cause of apparent differences may not be possible without studying the features of both programs in depth.

This report identifies cases where these apparent inconsistencies could occur, discusses plausible explanations for the apparent differences, and provides examples from the National Health and Nutrition Examination Survey (NHANES), the National Health Interview Survey (NHIS), and the Current Population Survey Annual Social and Economic Supplement (CPS-ASEC) to help demonstrate and discuss apparent differences. Discussion includes differences between aggregate-level analysis and record-level analysis, between polynomial and piecewise regression models, in how influential survey design factors (sample weights, variance units, and design-based degrees of freedom) are incorporated, in age-adjustment methods, in unit-level logistic regression using survey analysis software versus linear regressions on aggregated proportion estimates transformed to the log-odds scale as implemented in the Joinpoint software, and in the defaults, options, or settings of the two software packages.

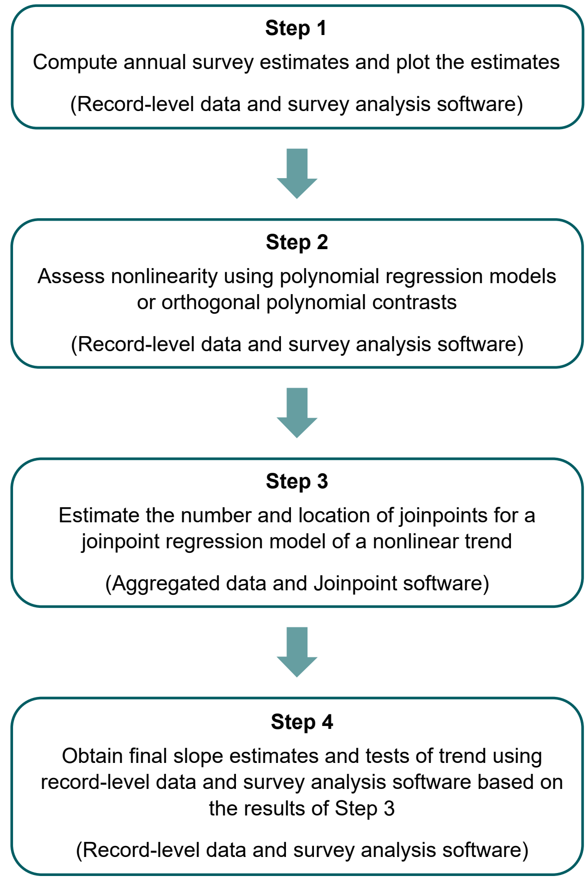
This report is focused on survey data and will not address any related or similar issues encountered with nonsurvey data, such as vital statistics data. Moreover, although some National Center for Health Statistics (NCHS) products, such as *Health, United States*, present tables compiled using aggregated data when record-level data are not readily available for analysis (for example, due to resource constraints or data use agreement requirements), this report focuses on cases where record-level analysis can be conducted. Per the "National Center for Health Statistics Guidelines for Analysis of Trends," analysts should try to conduct record-level analyses whenever possible (1).

Finally, this report focuses on the process that analysts use when conducting trend analyses and making decisions rather than on how results should be presented. It is not intended to be exhaustive or to provide specific solutions, as analysts may encounter many different scenarios. Instead, it provides recommendations, cautions, and information that analysts can use to make decisions during analysis.

Potential Differences

Figure 1 presents the general approach suggested by the "National Center for Health Statistics Guidelines for Analysis of Trends" when using record-level data to conduct trend analyses of survey data. This approach uses survey analysis software such as SUDAAN, the R survey package, STATA, or SAS/STAT survey procedures to compute estimates and assess nonlinearity of record-level data (steps 1, 2, and 4) and evaluates the number and location of joinpoints using the Joinpoint software (step 3).

Figure 1. General approach for conducting trend analyses of record-level survey data



NOTE: Approach suggested by "NCHS Guidelines for Analysis of Trends."
SOURCE: National Center for Health Statistics.

In some cases, analysts may observe different results based on the survey analysis software compared with the Joinpoint software. This means that the model indicated in Figure 1, step 3 may differ from the model indicated in Figure 1, steps 1 and 2 or from the model indicated in Figure 1, step 4. For example, the joinpoints identified by the Joinpoint software (step 3) may not be statistically significant when the prespecified model is estimated in the survey analysis software (step 4). Many plausible explanations for these inconsistencies exist, and some are worked through in the following sections. Differences that may be observed in the magnitude of the point estimates or standard errors are not discussed because Issue 12 in the "National Center for Health Statistics Guidelines for Analysis of Trends" recommends using the Joinpoint software to estimate the number and location of the joinpoints, not to obtain slope or variance estimates for analysis of survey data (1).

Figure 2 and Table A identify instances in the analysis process where analysts may observe inconsistencies between the survey analysis software and the Joinpoint software. The two diagrams also point readers to potential explanations for these inconsistencies, which are described in subsequent sections. The remainder of the report is divided into six main sections:

1. In "Consistent Results," two ideal examples which demonstrate no apparent inconsistencies are presented; one example has multiple joinpoints and one does not have any.
2. In "Polynomial Versus Piecewise Regression: Similarities and Differences," polynomial regression models and piecewise regression models are compared because differences between the two types of models sometimes contribute to differences between the results observed in steps 2 and 3 (Figure 1) of the analysis process.
3. In "Age-adjustment methods," brief descriptions of direct age adjustments (recommended by the "National Center for Health Statistics Guidelines for Analysis of Trends" for steps 2 and 3 of Figure 1) and alternative age-adjustment methods (recommended for step 4 of Figure 1) are presented with an explanation of when and why both methods are useful.
4. In "Influential Survey Design Factors," factors such as survey weights, variance–covariance matrices, and design-based degrees of freedom, which are handled differently by the survey analysis software (using record-level analysis) versus the Joinpoint software (using aggregate-level analysis) are discussed. Additionally, updates to the way NCI Joinpoint software incorporates variance–covariance matrices are presented.
5. In "Explanations That Are Less Common," other plausible explanations for the differences observed between the survey analysis software and the Joinpoint software are presented. These include too few datapoints, differences in the methods used across software packages, differences in the methods used within the same software package, deviations in the typical procedure used by analysts due to outside knowledge, and unusual attributes of the data.
6. In "One Answer Is Not Always Enough," the intersection of the explanations described in previous sections is discussed.
7. The final section, "Frequently Asked Questions," provides responses to frequently asked questions.

Worked examples are incorporated into the sections with details presented in Appendix I. All examples follow the approach suggested in "National Center for Health Statistics Guidelines for Analysis of Trends" and outlined in Figure 1.

Consistent Results

Ideally, results produced by the Joinpoint software are congruent with the results produced by the survey analysis software; that is, the number and location of joinpoints identified by the Joinpoint software match the number and location of statistically significant joinpoint coefficients estimated by the survey analysis software in the prespecified segmented regression model. Naturally, because the Joinpoint software fits models based on aggregate-level estimates and survey analysis software fits models based on record-level data, this occurs when aggregate-level models and record-level models both identify the same number of statistically significant joinpoints. This section provides two examples where the results between the two software programs (or two models) are consistent.

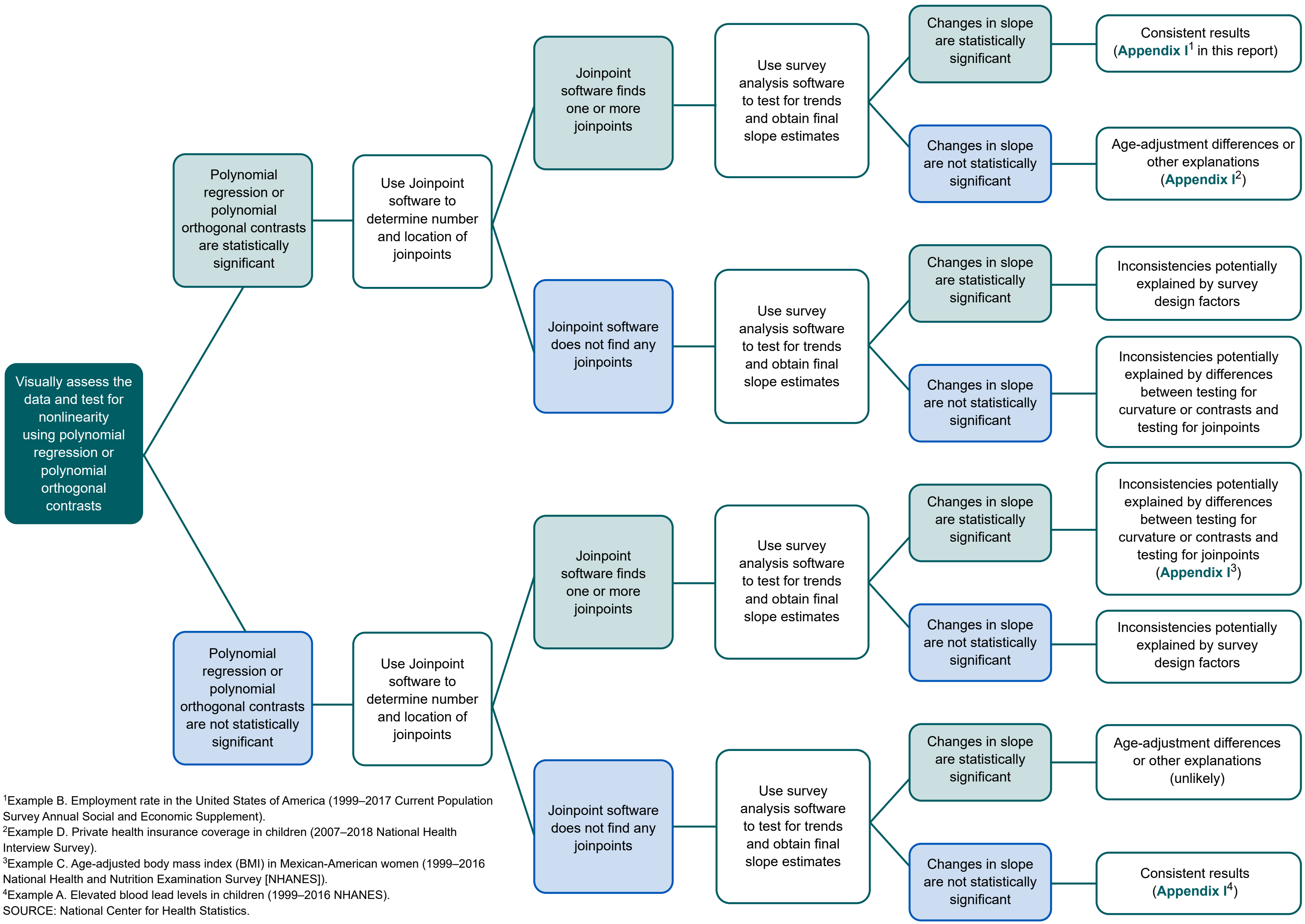
Example A in Appendix I presents the trendline by 2-year survey cycle for elevated blood lead levels (greater than or equal to 5 µg/dL) in children ages 1–11 from the 1999–2016 NHANES. In this example, the logistic regression using SUDAAN is statistically significant, higher-order terms are not statistically significant using SUDAAN, and the Joinpoint software also suggests a linear trend with no joinpoints. Therefore, results are consistent across software programs in terms of the number of statistically significant joinpoints in the final model.

Example B in Appendix I presents yearly employment rates from the 1999–2017 CPS-ASEC collected by the U.S. Census Bureau. The employment rate represents people age 16 and older in the U.S. labor force who are employed. The labor force is defined as people who have a job and people who are jobless, looking for a job, and available for work. In this example, both the quadratic and cubic regressions are statistically significant using SAS PROC SURVEYREG, the Joinpoint software identifies joinpoints at 2002, 2006, and 2009, and the piecewise regression model identified with the Joinpoint software with joinpoints at 2002, 2006, and 2009 displays statistically significant changes in slope between all adjacent slope estimates when estimated using SAS PROC SURVEYREG. A statistically significant decline was seen from 1999 to 2002 (96% to 94%), a statistically significant increase from 2002 to 2006 (94% to 95%), a statistically significant decline from 2006 to 2009 (95% to 90%), and a statistically significant increase from 2009 to 2017 (90% to 96%). These results are consistent across software programs.

Polynomial Versus Piecewise Regression: Similarities and Differences

"National Center for Health Statistics Guidelines for Analysis of Trends" recommends that, before using the Joinpoint software or fitting a piecewise regression model using a survey package, the data be screened for nonlinearity by performing a polynomial regression or testing the statistical

Figure 2. Decision flow chart for analyzing trends of survey data for all possible scenarios



[1]Example B. Employment rate in the United States of America (1999–2017 Current Population Survey Annual Social and Economic Supplement).
[2]Example D. Private health insurance coverage in children (2007–2018 National Health Interview Survey).
[3]Example C. Age-adjusted body mass index (BMI) in Mexican-American women (1999–2016 National Health and Nutrition Examination Survey [NHANES]).
[4]Example A. Elevated blood lead levels in children (1999–2016 NHANES).
SOURCE: National Center for Health Statistics.

Table A. Analyzing trends of survey data: An explanation for all possible scenarios

Possible scenarios	Polynomial statistically significant: Joinpoint software finds a joinpoint	Polynomial statistically significant: Joinpoint software does not find a joinpoint	Polynomial not statistically significant: Joinpoint software finds a joinpoint	Polynomial not statistically significant: Joinpoint software does not find a joinpoint
Piecewise regression statistically significant based on survey analysis software	Consistent Example B, Appendix I Employment rate in the United States of America (1999–2017 Current Population Survey Annual Social and Economic Supplement)	Potentially explained by influential survey design factors such as sample weights, the full variance-covariance structure, and degrees of freedom	Potentially explained by differences between testing for curvature or contrasts and testing for joinpoints Example C, Appendix I Age-adjusted body mass index (BMI) in Mexican-American women (1999–2016 NHANES)	Differences across age-adjustment techniques or other explanations Unlikely outcome because the estimated piecewise regression model using the survey analysis software is typically prespecified by Joinpoint software
Piecewise regression not statistically significant based on survey analysis software	Differences across age-adjustment techniques or other explanations Example D, Appendix I Private health insurance coverage in children (2007–2018 National Health Interview Survey)	Potentially explained by differences between testing for curvature or contrasts and testing for joinpoints	Potentially explained by influential survey design factors including sample weights, the full variance-covariance structure, and degrees of freedom	Consistent Example A, Appendix I Elevated blood lead levels in children (1999–2016 NHANES)

NOTE: NHANES is National Health and Nutrition Examination Survey.

SOURCE: National Center for Health Statistics, 2025.

significance of orthogonal polynomial contrasts. This screening is used to help determine whether piecewise regression models should be considered. While the screening is informative, polynomial regression and piecewise regression are different models. The Joinpoint software does not fit polynomial regression models or test orthogonal polynomial contrasts. Therefore, in some cases, differences between the results observed using survey analysis software and the results observed using the Joinpoint software are explained by differences in the basic characteristics of polynomial versus piecewise regression models. Specifically, this could occur if the Joinpoint software finds a joinpoint and the estimated piecewise regression model using the survey package indicates statistically significant changes in slope, but the polynomial regression terms or orthogonal polynomial contrasts used to screen for nonlinearity are not statistically significant. Similarly, screening for nonlinearity may produce statistically significant polynomial regression terms or orthogonal polynomial contrasts, but subsequent analyses using the Joinpoint software to identify joinpoints and survey analysis software to build piecewise regression models may suggest that only the linear model is statistically significant.

While both polynomial regression and piecewise regression techniques model nonlinear variations of the basic linear regression model, they are distinct models, characterizing distinct shapes. In the case of a trend analysis, a second-order polynomial regression model (quadratic) models a broad curve across time, a third-order polynomial regression model (cubic) models two broad curves across time, a fourth-order polynomial regression model (quartic) models three broad curves across time, etc. In contrast, piecewise regression models, as identified by the Joinpoint software, model trends in which a change in slope occurs at one (or more) point(s) in time. Of course, depending on the shape of the data, large differences between polynomial regression and piecewise regression models may not exist, and it may not always be clear which model offers a better fit, particularly as the order of the polynomial regression model increases. Furthermore, piecewise regression models are often preferred because they are easier to interpret than polynomial regression models and provide greater flexibility in modeling the diverse forms that trends can take.

Similarly, polynomial regression models generally align with comparisons of orthogonal polynomial contrasts. However, as polynomial regression is distinct from piecewise regression, polynomial regression is distinct from orthogonal polynomial contrasts. Regression models postulate that a probability distribution of the outcome variable exists for each level of a predictor variable, and that the means of these probability distributions vary in a systematic fashion as the values of the predictor variables change. Contrasts compare factor level means, which may or may not include multiple levels of predictor variables and are driven by pairwise comparisons. Often orthogonal polynomial contrasts are designed to mimic the polynomial regression, but they are not always identical (2).

Example C in Appendix I presents age-adjusted estimates of body mass index (BMI) in Mexican-American women from the 1999–2016 NHANES. In this example, higher-order polynomial terms are not statistically significant when estimated in SUDAAN, the Joinpoint software suggests a joinpoint at the 2009–2010 survey cycle, and a piecewise regression in SUDAAN using the model identified by the Joinpoint software indicates that the change in the slopes of the two segments around the 2009–2010 time point is statistically significant. In this case, the inconsistency between step 2 and steps 3 and 4 (Figure 1) is likely due to differences between modeling a nonlinear polynomial (quadratic) curve and modeling two linear line segments in a piecewise regression model. As explained in subsequent sections, it could also be influenced by differences between the Bayesian Information Criterion (BIC) used by the Joinpoint software and the traditional *t* tests used to estimate changes between successive slopes in SUDAAN. The final piecewise regression model from step 4 (Figure 1) indicates that the age-adjusted mean BMI in Mexican-American women increased at an average rate of 0.18 per survey cycle (about 0.09 per year) between 1999–2000 and 2009–2010 and at an average rate of 0.65 (about 0.32 per year) per survey cycle between 2009–2010 and 2017–2018.

Age-adjustment Methods

Age adjustment is a technique used to adjust for the changing age structure in study populations by calibrating to a standard population so that all the time periods' populations have the same age structure as the standard population. When health indicators are related to age, changes in the underlying age structure of the study population may confound differences observed in the indicator over time. Basic age adjustments help minimize these effects (3–5).

The descriptive procedures in survey analysis software, such as SUDAAN and others, use a direct age adjustment performed by applying age-specific rates in a population of interest to a standardized age distribution. For example, age-adjusted rates calculated by the direct method are:

$$\sum_{i}^{n} r_i \left(\frac{p_i}{P}\right)$$

where

r_i = rate in age group i in the population of interest,

p_i = standard population in age group i,

$$P = \sum_{i}^{n} p_i$$

and n = total number of age groups over the age range of the age-adjusted rate.

Consequently, aggregate estimates that are read into the Joinpoint software have been estimated using a direct age adjustment. However, SUDAAN and other survey analysis software have no available techniques for incorporating direct age adjustment into commonly used inferential procedures for record-level data, such as SUDAAN PROC REGRESS. Therefore, for trend analyses of survey data, the final estimated model using record-level data and survey analysis software must incorporate alternative age-adjustment methods, namely 1) age adjustment of survey sample weights, or 2) using age as a covariate in the final regression models (6). Subtle differences between the direct method used to produce aggregated estimates for the Joinpoint software and the alternative methods used to estimate the final piecewise model using the survey analysis software could cause apparent differences between the Joinpoint software and the survey analysis software. The "National Center for Health Statistics Guidelines for Analysis of Trends" recommends the first approach, age adjustment of survey sample weights, when fitting the final piecewise model using the survey analysis software (1).

In Example C, Appendix I, the final piecewise regression model is estimated using age-adjusted survey sample weights as recommended by the "National Center for Health Statistics Guidelines for Analysis of Trends." However, if age-adjusted sample weights are used throughout this example for the sake of consistency between the survey analysis software and the Joinpoint software, instead of using a direct age adjustment in step 1 (Figure 1) (as recommended by the "National Center for Health Statistics Guidelines for Analysis of Trends"), conclusions and results are similar with a placement of the joinpoint at 2011–2012 instead of 2009–2010 (results not shown).

Influential Survey Design Factors

When the results for nonlinearity with polynomial regression or orthogonal polynomial contrasts match the piecewise regression model determined using the survey analysis software but do not align with the number of joinpoints suggested by the Joinpoint software, the differences observed across packages may be explained by design factors. Design factors, including sample weights, the full variance–covariance structure, and design-based degrees of freedom, are accounted for in SUDAAN and other survey analysis software, but are not always accounted for when using design-based estimates in the Joinpoint software. Issue 5 of the "National Center for Health Statistics Guidelines for Analysis of Trends" discusses how ignoring the design factors can affect the analysis. That explanation is reiterated here, ways the Joinpoint software has been updated since the "National Center for Health Statistics Guidelines for Analysis of Trends" was published are discussed, and readers are pointed to three sources for guidance on how to use the updated Joinpoint software in conjunction with survey analysis software when a logistic model will be used to obtain final trend estimates.

Sampling weights must be used for the estimates along the trend line to be representative of the population (7,8). To mitigate some of the limitations of conducting a piecewise regression analysis using aggregated data, as is done with the Joinpoint software, it is recommended that the point estimates and their variances be computed using record-level data and survey analysis software first, before being transferred into the Joinpoint software. If sample weights are used properly, the estimate of the slope of a trend obtained using record-level survey data and the estimate obtained using aggregated survey data tend to be similar, because the estimates along the trend line are similar. However, slight differences between the two could be observed, resulting in nonidentical trend lines, because in each package analysts estimate the same trend line using slightly different estimators. This scenario is illustrated in depth in Appendix I of the "National Center for Health Statistics Guidelines for Analysis of Trends" (1).

The full variance–covariance structure is important when estimating the variance of the slope of a trend, particularly when analyzing surveys for which some primary sampling units (PSUs) are in the sample for multiple years (for example, NHIS). When this type of year-to-year correlation is present, failure to incorporate the full variance–covariance structure of the data in a trend analysis can result in incorrect estimates of the variance of the slope. When the variance of the slope is underestimated, test statistics tend to be overestimated, which can result in an analyst concluding that a model or change in slopes is statistically significant, when in fact the low *p* value is simply an artifact of an underestimated variance of the slope. Early versions of the Joinpoint software were not able to incorporate the full variance–covariance structure of survey (or nonsurvey) data. For analyses conducted using these versions, instances where the Joinpoint software suggests a joinpoint but survey analysis software does not may be attributable to the variance–covariance matrix, particularly if the *p* value is very close to the 0.05 (or otherwise defined) threshold. Now analysts can incorporate the variance–covariance matrix by using Joinpoint software version 4.9.0.0 or later. Instructions on how to do this are provided in the NCI Joinpoint Regression Software Help System on the NCI website (9).

As pointed out by the "National Center for Health Statistics Guidelines for Analysis of Trends," if the Joinpoint software is used to identify joinpoints and a logistic model is used to obtain final estimates of trends, the proportions (or predictive margins if the trend model includes covariates) and their standard errors should be transformed to the log-odds scale before inputting them into the Joinpoint software (1). Because the "National Center for Health Statistics Guidelines for Analysis of Trends" was published before Joinpoint software version 4.9.0.0 was released, the report does not provide information on how to transform the variance–covariance matrix to the log-odds scale. Appendix II in this report outlines how to transform the original variance–covariance matrix for a series of *n* estimated proportions $\hat{p}_i, \hat{p}_{i+1}, \dots, \hat{p}_{i+(n-1)}$ collected at time points *i* through $\{i+(n-1)\}$ into a variance–covariance matrix for

$$\ln\left(\frac{\hat{p}_1}{1-\hat{p}_1}\right), \ln\left(\frac{\hat{p}_2}{1-\hat{p}_2}\right), \dots, \ln\left(\frac{\hat{p}_{i+(n-1)}}{1-\hat{p}_{i+(n-1)}}\right) \quad \text{[log-odds scale]}$$

Appendix III provides guidance on how to implement this transformation using SUDAAN, SAS/STAT survey procedures, and SAS PROC IML. The steps outlined in Appendix III can be generalized for use in any survey analysis software. Appendix IV provides an example showing the transformation using data from the 2007–2018 NHIS, Family Core component.

Surveys that do not visit the same location during each collection year or survey cycle sometimes assume independence of PSUs and strata across time. In this case, no overlap in PSU and strata variables across time exists, and, therefore, the covariance terms in the variance–covariance matrix associated with estimates across time are zero. This is the case for public-use NHANES data files, for example, and can be checked in any data set by producing cross-tabulations of the design variables over time.

Finally, for NCHS surveys, the recommended number of degrees of freedom for a hypothesis test is generally the number of PSUs minus the number of sampling strata. For aggregated data, as is used with the Joinpoint software, the number of degrees of freedom is typically a function of the number of observed time points in the analysis and the number of parameters estimated. Therefore, for NCHS surveys, the number of degrees of freedom using the record-level data analysis (survey package) will be substantially larger than the number for an aggregated data analysis (the Joinpoint software). Differences in the number of degrees of freedom can easily influence test statistics and *p* values, consequently influencing if an analyst concludes that a result is statistically significant or not.

Explanations That Are Less Common

In other instances, it may not be clear why differences are observed between the survey analysis software and the Joinpoint software. Possible explanations include too few datapoints, differences in the methods used across software packages, differences in the methods used within the same software package, deviations in the typical procedure used by analysts due to outside knowledge, or simply unusual attributes of the data.

Occasional differences in results are common when different software packages, with different defaults, different assumptions, and different processes are compared with one another, particularly if the results produced are very close to the threshold of decision making (for example, $\alpha = 0.05$ for statistical significance). For example, it is common for the estimates produced by SAS PROC SURVEYMEANS in SAS to deviate slightly from comparable estimates produced by SUDAAN (10) or the R survey package. In this case, a distinction also exists between the model selection criterion used by the Joinpoint software to determine the optimal number of joinpoints and the decision-making process used when fitting a prespecified model with the survey design software, which focuses on using traditional *t* tests to estimate changes between successive slopes. The permutation test and BIC use the entire time series to determine the best number of joinpoints, while segment-wise testing uses only segment-specific observations.

Differences across seemingly identical models within the same statistical package are also common when different options and settings are used to build the model. For example, the Joinpoint software includes multiple model selection techniques for identifying joinpoints, including a sequence of permutation tests (11) and BIC (12,13). Because the permutation tests and BIC use different algorithms to estimate the number and location of joinpoints, they may identify different numbers of joinpoints and the joinpoints identified may be located at different time points, particularly for trends with volatility or subtle changes in trend. Specifically, the permutation test is generally considered more conservative than BIC. Therefore, the Joinpoint software is more likely to identify a joinpoint if the BIC method is used. Moreover, times occur when the Joinpoint software recommends a joinpoint even though the *t* test for a change in slopes (in the Joinpoint software) is statistically insignificant. In this case, the *t* test used to produce the *p* value for a change in slopes relies on asymptotic normality, while the permutation test produces an exact *p* value (14). The "National Center for Health Statistics Guidelines for Analysis of Trends" recommends using the permutation test for model selection if 10 or more time points are used, and BIC if fewer than 10 time points are used or if analysts use predictive margins to incorporate covariates. For more information regarding parameter selection, which options to use, and when to consider changing the defaults in the Joinpoint software, see the "National Center for Health Statistics Guidelines for Analysis of Trends" (1) and "Guidance for Selecting Model Options in the National Cancer Institute Joinpoint Regression Software" (15).

Differences across packages could also be observed in instances where prior knowledge, a change in health policy, visual inspection, or other information causes analysts to deviate from the normal processes of decision making, such as whether to pursue a piecewise regression model using SUDAAN or other survey analysis software, despite observing statistically insignificant results using the Joinpoint software. In this case, the data may not strongly reflect what the analyst knows is true based on other research, but enough of an effect may exist to be picked up by one statistical package and not another.

Identifying joinpoints can also be challenging when few time points are available. NCI recommends not using any joinpoints when a user has fewer than seven time points (Table B). In this case, analysts may rely exclusively on results from the survey analysis package.

Similarly, trends may appear inconsistent across software packages if the analyst conducts an analysis on a small subset of record-level data, such as specific sex, age, or racial-ethnic domains. In this case, large standard errors may lead to unstable estimates at one or more time points, and slight model changes across packages may appear larger

Table B. Recommended maximum number of joinpoints based on the number of time points using Joinpoint software

Number of time points	Default maximum number of joinpoints
0–6	0
7–11	1
12–16	2
17–21	3
22–26	4
27–31	5
32–36	6
37 or more	7

SOURCE: National Cancer Institute Joinpoint Help System (see reference 20 in this report).

than if the analyst had access to a more robust data set for that subdomain.

Finally, as stated previously, if the results produced are close to the predetermined threshold for statistical significance (such as p close to 0.05), then fluctuations between statistically significant results and statistically insignificant results are common. Differences seen across statistical packages or across models may be due to the effect being only moderately strong and ultimately indeterminate, or due to a small variance estimate relative to the beta coefficient. In these cases, other factors, such as the absolute difference in beta coefficients or the size of variance estimates relative to beta coefficients, can be considered along with the *p* value as evidence for or against retaining a joinpoint in a regression model (16–18).

Example D in Appendix I presents the percentage of U.S. children age 17 and younger who had a private health insurance plan at the time of interview using data from the 2007–2018 NHIS (19). In this example, the tests for quadratic and cubic trends are both statistically significant, and the Joinpoint software suggests two joinpoints (2010 and 2013). However, when the piecewise regression model suggested by the Joinpoint software is estimated using the R survey package, the change in slopes between segments two and three (at 2013) is not statistically significant. In this case, the inconsistency between steps 1–3 and step 4 (Figure 1) are likely due to differences in the model selection criterion for the BIC test (the Joinpoint software) versus the segment-wise *t* test (R survey package); BIC uses the entire time series, while the segment-wise testing uses only segment-specific observations. Defaulting to the R survey package, the final piecewise regression model indicates that the percentage of U.S. children age 17 and younger who had private health insurance at the time of interview decreased from 2007–2010 and then was stable from 2010–2018.

One Answer Is Not Always Enough

In most cases, inconsistencies between the Joinpoint software and survey analysis software are attributed to differences between polynomial and piecewise regression, survey design factors (that is, sampling weights, full variance–covariance structure, and degrees of freedom), differences between software settings or packages, or changes in the common approach taken by analysts. However, situations are often complex, and inconsistencies cannot always be attributed to one easily identified solution. Sometimes inconsistent results across the packages result from a variety of factors. Example C in Appendix I demonstrates an instance where differences between polynomial and piecewise regression curves may be intersecting with age-adjustment methods to create differences between the results from SUDAAN versus the results from the Joinpoint software. Example C may also be influenced by differences between traditional BIC and the traditional *t* tests used to estimate changes between successive slopes. Similarly, instances may exist where differences between the results from SUDAAN versus the results from the Joinpoint software may be explained by the fact that the Joinpoint software does not account for survey design factors, as well as the fact that the Joinpoint software was explicitly created for long trend lines with many time points; or, an instance might exist where knowledge about an influential policy change helps explain the differences observed between SUDAAN and the Joinpoint software, but differences between polynomial and piecewise regression curves may also be influencing the results. The fundamental differences described in this report are intended to help analysts consider results thoroughly and move forward with the analysis in a defendable way. This does not mean that every inconsistency will be easily traced to one (and only one) of the explanations described above.

Frequently Asked Questions

Why do results from the Joinpoint software sometimes include joinpoints that are not statistically significant when the same model is evaluated with a survey package?

Inconsistencies between the Joinpoint software and survey analysis software regarding the number and placement of joinpoints are a result of 1) different testing procedures between the two software packages, 2) different methods for capturing survey design factors, and 3) differences between individual- and aggregate-level analysis. In terms of testing procedures, depending on the data structure, the Joinpoint software uses various model selection methods (such as a sequence of permutation tests or BIC) to determine both the number and placement of joinpoints. This is a more comprehensive procedure than the survey package approach of testing the difference between two slopes using a *t* test once a joinpoint has already been located. In terms of survey design factors, the Joinpoint software is currently limited to using only aggregated weighted estimates and either their standard errors or a variance–covariance matrix to determine the number and placement of joinpoints. It does not use record-level data or the proper design-based degrees of freedom.

What design factors are accounted for in SUDAAN and other survey design software that are not accounted for when design-based estimates are used in the Joinpoint software?

Design factors that are accounted for in SUDAAN and other survey design software include sample weights, the full variance–covariance structure, and design-based degrees of freedom. In the Joinpoint software, sample weights are accounted for indirectly because survey design software is used to calculate the aggregated estimates and standard errors or variance–covariance matrix before data entry. However, clear differences exist between aggregate-level analysis and record-level analysis, and survey degrees of freedom cannot be specified directly or indirectly in the Joinpoint software. More complete descriptions of survey design factors are provided below and in Issue 5 of the "National Center for Health Statistics Guidelines for Analysis of Trends."

Sample weights

Sample weights must be used so that the estimates along the trend line are representative of the population (see section 3.5 of Korn and Graubard [7] and Chapter 7 of Heeringa et al [8]). To mitigate some of the limitations of conducting a piecewise regression analysis using aggregated data, as is used with the Joinpoint software, the "NCHS Guidelines for Analyses of Trends" recommends that point estimates and their variances be computed using record-level data and survey analysis software first, thereby incorporating the sample weights and design variables into the aggregated estimates before they are transferred into the Joinpoint software.

The full variance–covariance structure

The full variance–covariance structure is important when estimating the variance of the slope of a trend, particularly when analyzing surveys for which some PSUs are in the sample for multiple years (for example, NHIS). When this type of year-to-year correlation is present, failure to incorporate the full variance–covariance structure of the data in a trend analysis may result in inaccurate estimates of the variance of the slope. Specifically, positive correlation between survey years or cycles leads to variance estimates that are too small, and when the variance of the slope is underestimated, test statistics tend to be overestimated. Therefore, positive correlation often leads to overestimated test statistics.

Earlier versions of the Joinpoint software were not able to incorporate the full variance–covariance matrix, but this functionality was added to version 4.9.0.0 and later updates. See Appendix II, Appendix III, and Appendix IV for guidance on how to incorporate the variance–covariance matrix into the Joinpoint software when logistic regression will be used to model a time trend using survey data.

Degrees of freedom

For population-based NCHS surveys, the recommended nominal degrees of freedom for a hypothesis test is generally the number of PSUs minus the number of sampling strata. For aggregated data, as is used with the Joinpoint software, it is typically a function of the number of observed time points in the analysis and the number of parameters estimated. Therefore, for NCHS surveys, the number of degrees of freedom using the record-level data analysis (survey package) will be substantially larger than the number for an aggregated data analysis (the Joinpoint software).

Note to analysts

It is hard to know in advance when these types of design issues, such as year-to-year correlation, will influence results. Rather than try to determine in advance whether the Joinpoint software results will be useful, it is best to proceed as usual and use this information to guide decisions when inconsistent results between packages are observed in terms of the number and placement of joinpoints.

What are the benefits of using the Joinpoint software with record-level survey data, given that analysts ultimately estimate and test the slopes of the line segments corresponding to the suggested joinpoints using a survey package (such as SUDAAN)?

Identifying a joinpoint through visual examination of the trend data may be possible, but more often the timing of a change is not obvious because the change is subtle or a volatility in the observed estimates exists. As described earlier, the Joinpoint software uses model selection methods (such as a sequence of permutation tests or BIC) to determine both the number and placement of joinpoints. This is a more comprehensive procedure than the survey package approach of testing the difference between two slopes using a *t* test once a joinpoint has already been located. Moreover, using the Joinpoint software in addition to survey analysis software may be useful for confirming unprecedented or surprising results. For analysis of survey data, the Joinpoint software should be used to estimate the number and location of joinpoints and survey analysis software should be used to conduct hypothesis tests of the difference between the slopes of adjacent line segments once a joinpoint has been determined.

How does SUDAAN calculate and use degrees of freedom differently compared with the Joinpoint software?

For NCHS surveys, the recommended nominal degrees of freedom for a hypothesis test is generally the number of PSUs minus the number of sampling strata. For aggregated data, as is used with the Joinpoint software, degrees of freedom is calculated as a function of the number of observed time points in the analysis and the number of parameters being estimated. For more information, see Issue 5 in the "National Center for Health Statistics Guidelines for Analysis of Trends" (1).

What software settings in the Joinpoint software, such as different options in the "Methods and Parameters" tab, should be used for survey data?

The Joinpoint software's documentation provides guidance on how to use the program and describes the different options, but no clear guidelines are given for choosing optimal settings (20). The choice of Joinpoint software settings when analyzing NCHS data are discussed in Issue 12 of the "National Center for Health Statistics Guidelines for Analysis of Trends" (1) and in a separate report, "Guidance for Selecting Model Options in the National Cancer Institute Joinpoint Regression Software" (15).

Do cases exist where it may not make sense to use the Joinpoint software?

In select instances, researchers analyzing survey data for trends may choose to ignore the results observed in the Joinpoint software or forego using the Joinpoint software altogether. For example, researchers with prior subject matter expertise or knowledge of a policy change in a particular year may choose to include a joinpoint in a piecewise regression model using survey analysis software, regardless of what the Joinpoint software suggests. In other instances, it may be challenging to identify joinpoints when few time points exist. NCI recommends not using any joinpoints when a user has fewer than seven time points (Table B). Therefore, analysts may need to decide between the standard procedure of a) using Joinpoint software to identify the number and placement of joinpoints before progressing to a record-level analysis by changing the maximum number of joinpoints the Joinpoint software will look for (this is not possible with version 4.7.0.0), or b) not using the Joinpoint software.

Similarly, if researchers are analyzing survey data, when would it make sense to ignore results given by the Joinpoint software?

Any of the reasons given earlier in the Frequently Asked Questions may also apply to this question. In addition, if, after visual inspection, the location of a joinpoint seems off by one or two time points (based on subject matter knowledge, or if the selected joinpoint does not line up with related trend lines), the suggested joinpoint may be moved if done in a principled and defendable way. One approach would be to move the joinpoint and re-test the difference between the adjacent slopes using a survey package, and then choose the joinpoint with the greatest amount of evidence based on the magnitudes of change, the confidence intervals or standard errors, and the *p* values. Another approach is to rely on the confidence intervals produced with the Joinpoint software for joinpoint placements (though not all design information is accounted for) (1,21).

Should analysts build and test a piecewise regression in the Joinpoint software or survey analysis software if they observe statistically insignificant results using polynomial models or orthogonal polynomial constrasts?

While polynomial regression and orthogonal polynomial contrasts generally produce nonlinearity assessments that are similar, the degree of nonlinearity identified by these two approaches may appear to be inconsistent with the number of joinpoints identified by piecewise regression models. This inconsistency reflects differences in the forms of nonlinearity the various approaches can detect, and, at times, the greater flexibility of the piecewise regression approach to model the diverse forms that trends take, as discussed in Issue 12 of "National Center for Health Statistics Guidelines for Analysis of Trends" (1). Therefore, if the visual display (step 1) suggests that a joinpoint exists, it is recommended that analysts test a piecewise regression model using the Joinpoint software or the survey analysis software despite the insignificant polynomial tests.

What is the benefit of checking for nonlinearity in SUDAAN or other survey analysis software before using the Joinpoint software?

Checking for nonlinearity in SUDAAN or another survey analysis software before using the Joinpoint software or the survey analysis software to build a piecewise regression model helps analysts gather a thorough understanding of the shape of the data and the options available for model building. In some cases, analysts may discover that a quadratic or other high-order polynomial may be a better fit for the data than the originally supposed piecewise regression model.

Conclusion

Given that a) a proper survey-based *t* test will not account for the fact that the placement of the joinpoint is not known, and b) the Joinpoint software is able to locate the placement of a joinpoint without fully accounting for all components of the survey design, the "National Center for Health Statistics Guidelines for Analysis of Trends" recommends two steps when analyzing record-level data. First, use the Joinpoint software to identify the number and placement of joinpoints using aggregated data. Second, use survey analysis software to run hypothesis tests of the differences between slopes of adjacent line segments to determine whether to retain all joinpoints. While the combined use of statistical survey software and the Joinpoint software gives analysts a better understanding of the shape and trend of the data, in practice seemingly inconsistent results may occur. As discussed in this report, several possible explanations for differences exist, including differences between polynomial and piecewise regression, incorporation of survey design features, and others. The detailed examples and frequently asked questions provide analysts with potential scenarios and guidance for decision making.

In all cases, analysts should document and provide a rationale for decisions. For example, when the *p* value is close to the significance threshold of α equal to 0.05 (such as when the *p* value is greater than or equal to 0.045 and less than or equal to 0.054), and the test statistic is on the border between the acceptance and rejection regions, analysts may decide to retain a statistically nonsignificant joinpoint, or vice versa (22). Similarly, visual inspections of the data, background information about known changes, or results from the tests for nonlinearity (such as polynomial regression or linear contrasts), may inform decisions. Importantly, if the results between the two software packages differ, the language in the results section of the report should be transparent and should clearly explain why a change in the trend line appears or does not appear, and discuss reasons why the results may not be conclusive.

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Appendix I. Illustrative Examples A through D

Example A. Elevated Blood Lead Levels in Children Ages 1–11 Years: NHANES, 1999–2016

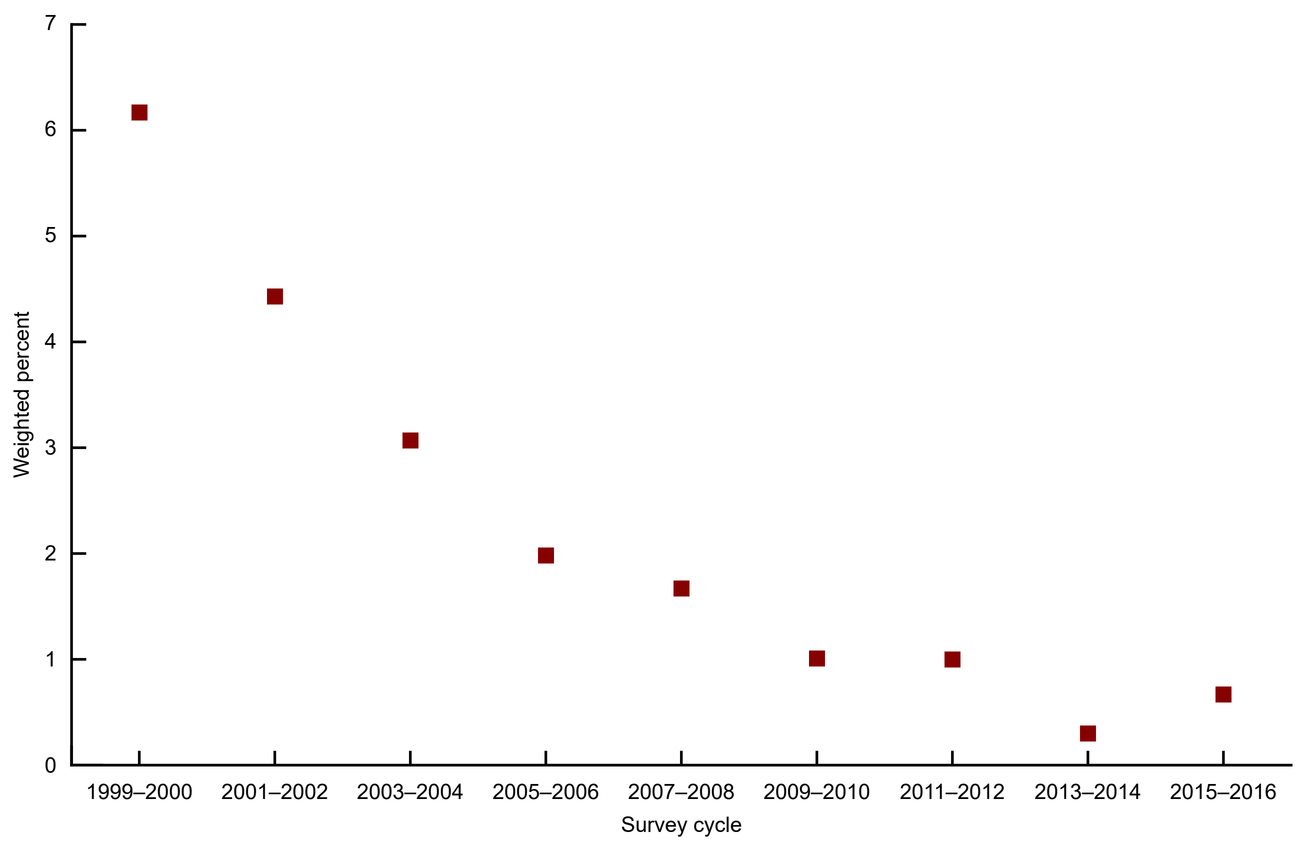
Overview

This example demonstrates a case in which the test for a linear trend in SUDAAN is statistically significant, higher-order terms are not statistically significant, and the National Cancer Institute's Joinpoint Regression Software also suggests a linear trend with no joinpoints. In this case, the two software programs agree in terms of the number and placement of joinpoints. Results are consistent. In most instances, this agreement between the two types of software is expected.

Step 1. Compute estimates for each survey cycle and plot the estimates

Weighted percentage estimates and standard errors by survey cycle in the National Health and Nutrition Examination Survey (NHANES), 1999–2016, are presented in Table I and Figure I. Estimates transformed to the log-odds scale are presented in Table I and Figure II.

Figure I. Prevalence of elevated blood lead levels in children ages 1–11 years who were examined at the mobile examination center



NOTES: Prevalence estimates and their standard errors were obtained using record-level data and SUDAAN's PROC DESCRIPT with mobile examination center weights. Elevated blood lead levels are 5 µg/dL or above.
SOURCE: National Center for Health Statistics, National Health and Nutrition Examination Survey, 1999–2016.

Table I. Prevalence estimates, transformed estimates, and standard errors by survey cycle of elevated blood lead levels in children ages 1–11 years who were examined at the mobile examination center

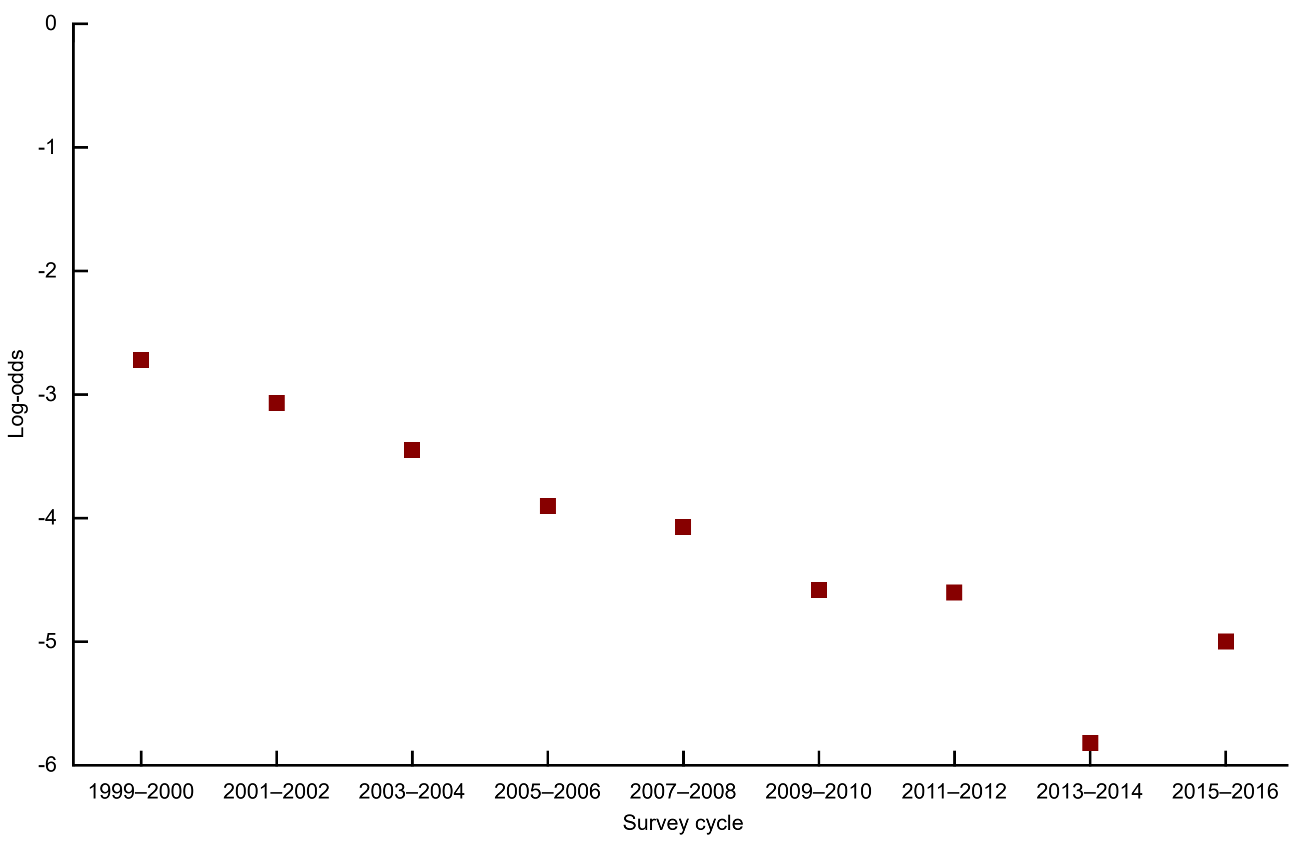
Survey cycle	*n*	Prevalence (weighted percentage)	Standard error	Transformed prevalence[1]	Transformed standard error[2]
1999–2000	1,611	6.17	1.20	-2.72	0.21
2001–2002	1,931	4.43	0.88	-3.07	0.21
2003–2004	1,754	3.07	0.89	-3.45	0.30
2005–2006	1,893	1.98	0.52	-3.90	0.27
2007–2008	1,813	1.67	0.52	-4.07	0.32
2009–2010	1,836	1.01	0.20	-4.58	0.20
2011–2012	1,750	1.00	0.37	-4.60	0.37
2013–2014	1,869	0.30	0.15	-5.82	0.50
2015–2016	1,802	0.67	0.30	-5.00	0.45

[1]Percentages were rescaled to proportions (p = percent/100) and then transformed to the log odds scale by applying the formula $\ln(p/(1-p))$.
[2]Standard errors of prevalence estimates were rescaled to be standard errors of proportions and then transformed to the log odds scale by applying the formula $se(p)/(p \bullet (1-p))$.

NOTES: Prevalence estimates and their standard errors were obtained using record-level data and SUDAAN's PROC DESCRIPT with mobile examination center weights. Elevated blood lead levels are 5 µg/dL or above.

SOURCE: National Center for Health Statistics, National Health and Nutrition Examination Survey, 1999–2016.

Figure II. Transformed prevalence estimates of elevated blood lead levels in children ages 1–11 years who were examined at the mobile examination center



NOTES: Percentage estimates and their standard errors were obtained using record-level data and SUDAAN's PROC DESCRIPT with mobile examination center weights. Weighted percentages were transformed to the log-odds scale to obtain transformed prevalence estimates. Elevated blood lead levels are 5 µg/dL or greater.
SOURCE: National Center for Health Statistics, National Health and Nutrition Examination Survey, 1999–2016.

Step 2. Initial assessment of nonlinearity: Polynomial regression or orthogonal polynomial contrasts

Estimates with standard errors are presented in Table II for the simple logistic regression model and quadratic logistic regression model.

Step 3. Estimate the number and location of joinpoints for nonlinear trends using Joinpoint software

For this example, the following options were selected in the Joinpoint software:

1. Log transformation: No
2. Heteroscedastic/correlated errors option: Variance–covariance matrix (provided)
3. Method: Grid search
    a. Minimum number of observations from a joinpoint to either end of the data: Two
    b. Minimum number of observations between two joinpoints: Two
    c. Number of points to place between adjacent observed *x* values in the grid search: Zero
4. Number of joinpoints:
    a. Minimum: Zero
    b. Maximum: One
5. Model selection method: BIC (fewer than 10 time points).

Automated output from the Joinpoint software (graph and model estimates) are presented in Figure III.

Step 4. Obtain final slope estimates and tests of trend using a standard survey package

Because neither SUDAAN nor Joinpoint software identifies a joinpoint, the simple logistic regression model (Table II) is chosen as the final model (Figure IV).

Conclusions

Based on SUDAAN, the best model for the data is the simple logistic regression presented in step 2 (Table II, Figure IV). In conclusion, the prevalence of high lead levels in children ages 1–11 decreased steadily between 1999–2000 and 2015–2016.

Explanation of differences

Results are consistent.

Table II. Logistic regression and quadratic regression estimates with standard errors of elevated blood lead levels in children ages 1–11 years who were examined at the mobile examination center

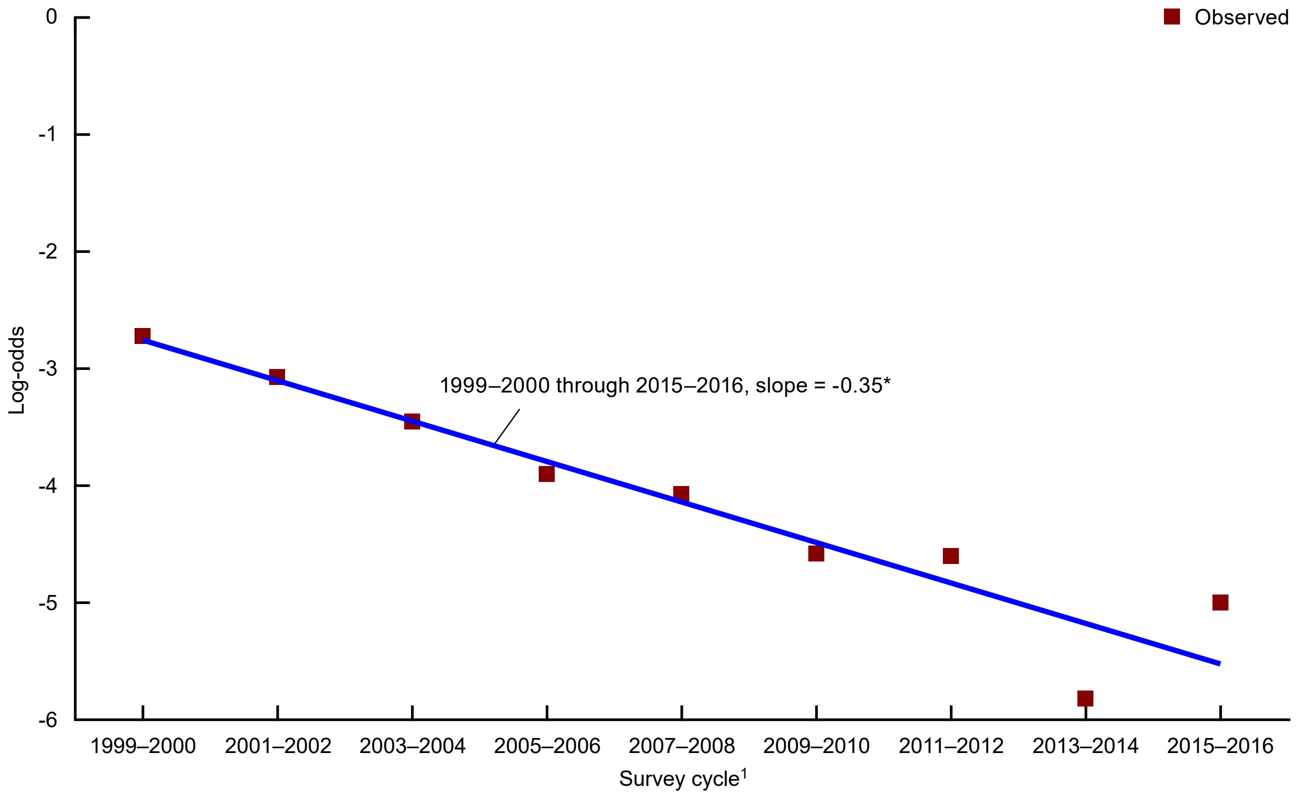
Model	β_0 (standard error) Intercept	β_1 (standard error) Survey cycle	β_2 (standard error) Survey cycle squared
Simple logistic regression	-2.40 (0.19)	-0.34 (0.04)	…
p values	< 0.0001	< 0.0001	…
Quadratic logistic regression	-2.29 (0.31)	-0.43 (0.17)	0.0097 (0.02)
p values	< 0.0001	0.0200	0.6200

… Category not applicable.

NOTES: Survey cycles 1999–2000 through 2015–2016 were coded as 1 through 9 for logistic regression analyses. Prevalence estimates and their standard errors were obtained using record-level data and SUDAAN's PROC RLOGIST. Elevated blood lead levels are 5 µg/dL or above.

SOURCE: National Center for Health Statistics, National Health and Nutrition Examination Survey, 1999–2016.

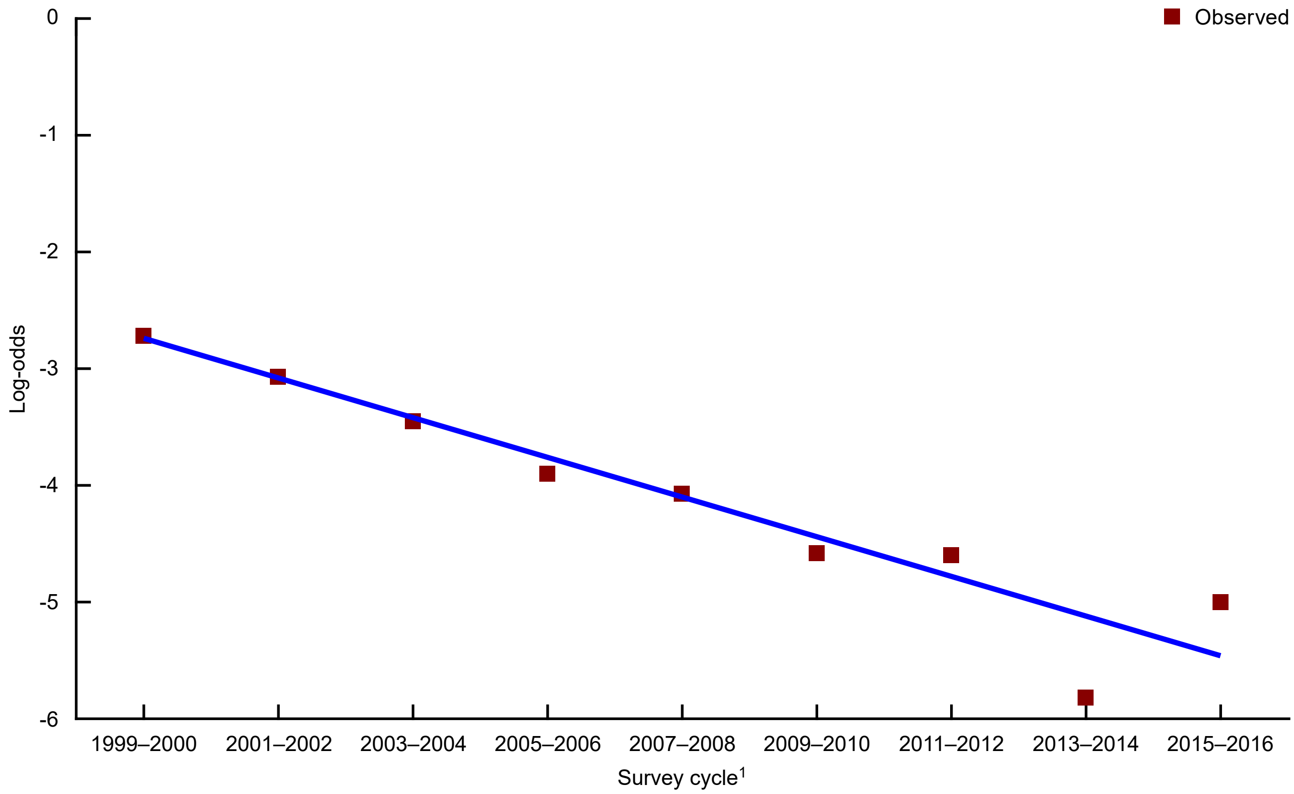
Figure III. Joinpoint software's automated output: Transformed estimates of elevated blood lead levels in children ages 1–11 years who were examined at the mobile examination center



* Indicates that the slope is significantly different from zero at the $\alpha = 0.05$ level. Final selected model has zero joinpoints.
[1]Survey cycles 1999–2000 through 2015–2016 were coded as 1 through 9 for logistic regression analyses.
NOTES: Transformed prevalence estimates and their standard errors were obtained using record-level data and SUDAAN's PROC DESCRIPT with mobile examination center weights. Elevated blood lead levels are 5 µg/dL.
SOURCE: National Center for Health Statistics, National Health and Nutrition Examination Survey, 1999–2016.

Model number	Number of joinpoints	Number of observations	Number of parameters	Degrees of freedom	Sum of squared errors	BIC
1	0	9	2	7	3.8983983	-0.3483831
2	1	9	4	5	3.3617172	-0.0082284

Figure IV. Transformed prevalence estimates of elevated blood lead levels with linear logistic regression line in children ages 1–11 years who were examined at the mobile examination center



[1]Survey cycles 1999–2000 through 2015–2016 were coded as 1 through 9 for logistic regression analyses.
NOTES: Observed prevalence estimates were obtained using record-level data and SUDAAN's PROC DESCRIPT with mobile examination center weights. For regression estimates, prevalence estimates and their standard errors were obtained using record-level data and SUDAAN's PROC RLOGIST. Elevated blood lead levels are 5 µg/dL or above. Linear logistic regression line shown is presented in Table II in this report.
SOURCE: National Center for Health Statistics, National Health and Nutrition Examination Survey, 1999–2016.

Example B. Employment Rate Among People Age 16 and Older in the U.S. Labor Force: 1999–2017 Current Population Survey Annual Social and Economic Supplements

Overview

This example demonstrates a case in which the test for a quadratic trend using SAS PROC SURVEY commands is statistically significant; a test for a cubic trend using SAS PROC SURVEY commands is statistically significant; the Joinpoint software suggests three joinpoints at 2002, 2006, and 2009; and the piecewise regression using SAS PROC SURVEY commands indicates that the changes in slope between all adjacent slope estimates are statistically significant. In this case, the results based on SAS PROC SURVEY commands match the results based on the Joinpoint software (in terms of the number and placement of joinpoints). Results are consistent. In most instances, this agreement between the two types of software is expected.

Step 1: Compute annual survey estimates and plot the estimates

Weighted proportions and standard errors by survey cycle are presented in Table III and Figure V.

Step 2: Initial assessment of nonlinearity: Polynomial regression or orthogonal polynomial contrasts

Estimates with standard errors are presented in Table IV for the simple linear regression model, quadratic regression model, and cubic regression model.

Step 3: Estimate the number and location of joinpoints for nonlinear trends using Joinpoint software

For this example, the following options were selected in the Joinpoint software:

1. Log transformation: No
2. Heteroscedastic/correlated errors option: Variance–covariance matrix (provided)
3. Method: Grid search
    a. Minimum number of observations from a joinpoint to either end of the data: Two
    b. Minimum number of observations between two joinpoints: Two
    c. Number of points to place between adjacent observed *x* values in the grid search: Zero
4. Number of joinpoints:
    a. Minimum: Zero
    b. Maximum: Three

Table III. Weighted proportions and standard errors by year of the employment rate among people age 16 and older in the U.S. labor force

Year	*n*	Weighted proportion	Standard error
1999	68,013	0.96	0.0009
2000	65,441	0.95	0.0010
2001	107,933	0.94	0.0009
2002	106,923	0.94	0.0009
2003	105,217	0.94	0.0009
2004	103,893	0.94	0.0009
2005	103,339	0.95	0.0008
2006	102,984	0.95	0.0008
2007	103,086	0.95	0.0009
2008	103,329	0.91	0.0011
2009	103,660	0.90	0.0011
2010	100,683	0.91	0.0011
2011	98,822	0.91	0.0011
2012	98,735	0.92	0.0010
2013	67,864	0.93	0.0012
2014	95,984	0.94	0.0009
2015	89,494	0.95	0.0009
2016	90,079	0.95	0.0008
2017	87,138	0.96	0.0008

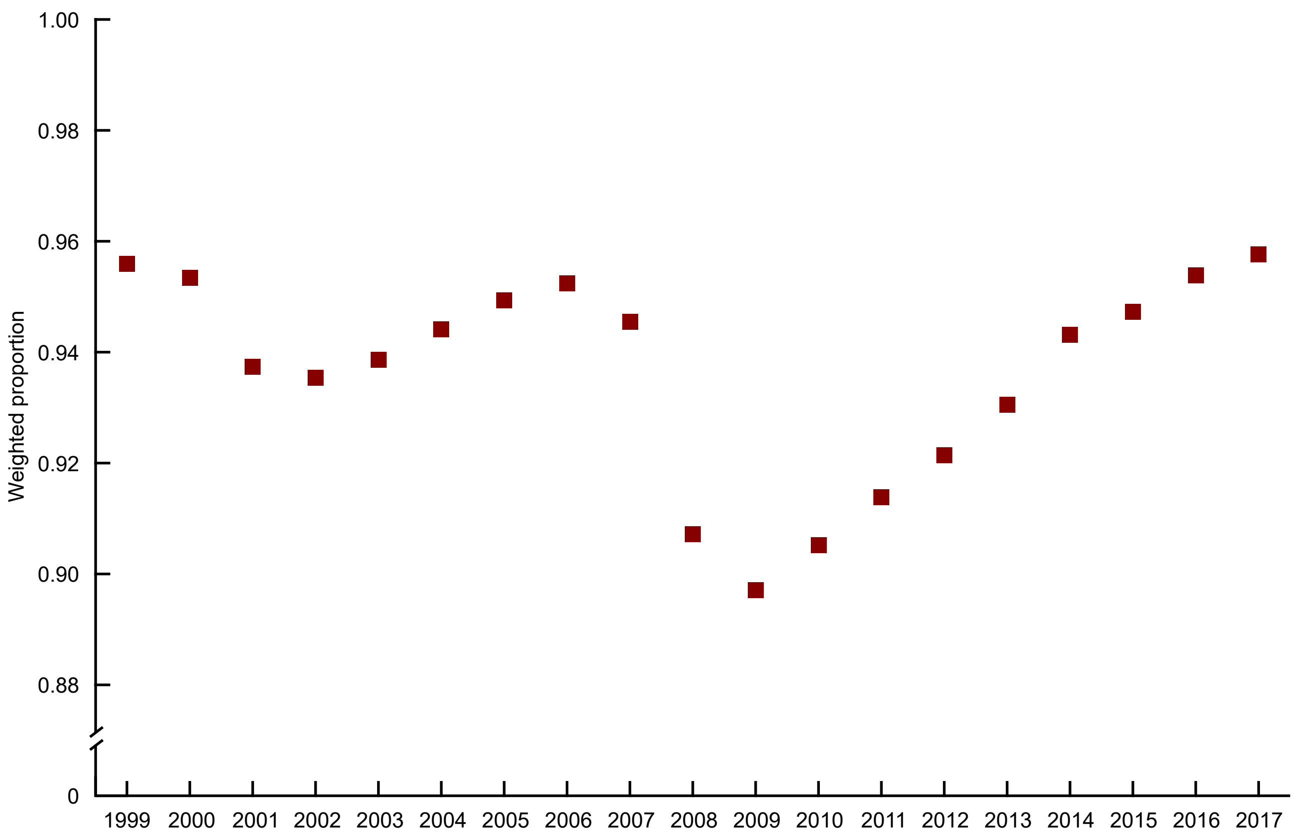
NOTES: Prevalence estimates and their standard errors were obtained using record-level data and PROC SURVEYMEANS in SAS. People are considered employed if they are employed during the survey week. Labor force includes people who have a job and people who are jobless, looking for a job, and available for work.

SOURCE: U.S. Census Bureau, Current Population Survey Annual Social and Economic Supplement, 1999–2017.

5. Model selection method: Permutation test (10 or more time points).

Automated output from the Joinpoint software (graph and model estimates) are presented in Figure VI.

Figure V. Employment rate among people age 16 and older in the U.S. labor force



NOTES: People are considered employed if they are empoyed during the survey week. Labor force includes people who have a job and people who are jobless, looking for a job, and available for work.
SOURCE: U.S. Census Bureau, Current Population Survey Annual Social and Economic Supplement, 1999–2017.

Table IV. Linear regression, quadratic regression, and cubic regression estimates with standard errors of the employment rate among people age 16 and older in the U.S. labor force

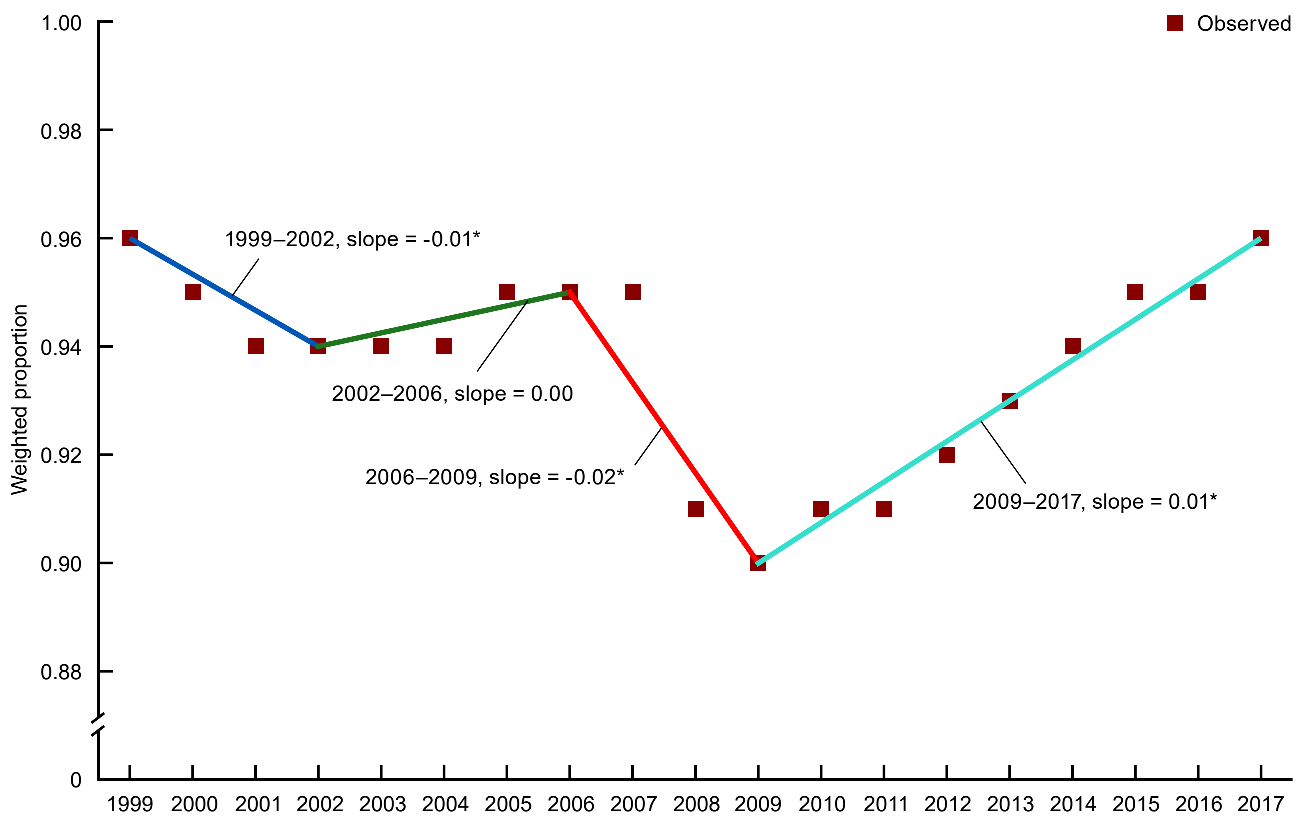
	β_0 (standard error)	β_1 (standard error)	β_2 (standard error)	β_3 (standard error)
Model	Intercept	Year	Year squared	Year cubed
Simple linear regression	0.94 (0.0004)	-0.0004 (0.00004)	…	…
p values	< 0.0001	< 0.0001	…	…
Quadratic regression	0.96 (0.0006)	-0.008 (0.0002)	0.0004 (0.000008)	…
p values	< 0.0001	< 0.0001	< 0.0001	…
Cubic regression	0.95 (0.0007)	0.001 (0.0003)	-0.001 (0.00005)	0.00005 (0.000002)
p values	< 0.0001	< 0.0001	< 0.0001	< 0.0001

… Category not applicable.

NOTES: Prevalence estimates and their standard errors were obtained using record-level data and PROC SURVEYREG in SAS. People are considered employed if they are employed during the survey week. Labor force includes people who have a job and people who are jobless, looking for a job, and available for work.

SOURCE: U.S. Census Bureau, Current Population Survey Annual Social and Economic Supplement, 1999–2017.

Figure VI. Joinpoint software's automated output: Employment rate among people age 16 and older in the U.S. labor force



* Indicates that the slope is significantly different from zero at the α = 0.05 level. Final selected model has three joinpoints.
NOTES: People are considered employed if they are empoyed during the survey week. Labor force includes people who have a job and people who are jobless, looking for a job, and available for work.
SOURCE: U.S. Census Bureau, Current Population Survey Annual Social and Economic Supplement, 1999–2017.

Test number	Null hypothesis	Alternate hypothesis	Degrees of freedom		Number of permutations	*p* value	Significance level
			Numerator	Denominator			
1.	0 joinpoint(s)	3 joinpoint(s)	6	11	4500	0.0002222	0.0166667
2.	1 joinpoint(s)	3 joinpoint(s)	4	11	4500	0.0002222	0.0250000
3.	2 joinpoint(s)	3 joinpoint(s)	2	11	4500	0.0126667	0.0500000

Step 4: Obtain final slope estimates and tests of trend using a standard survey package

Final estimates with standard errors for the prespecified model recommended by the Joinpoint software and obtained using SAS/STAT survey procedures are presented in Table V. A visual display is provided in Figure VII.

Conclusions

Based on SAS/STAT survey procedures, the best model for the 1999–2017 data is the piecewise regression model presented in step 4 (Table V, Figure VII). This corresponds to the model selected by the Joinpoint software and includes joinpoints at 2002, 2006, and 2009. In conclusion, the employment rate declined steadily between 1999 and 2002, increased steadily between 2002 and 2006, declined sharply between 2006 and 2009, and increased steadily between 2009 and 2017.

Explanation of differences

Results are consistent.

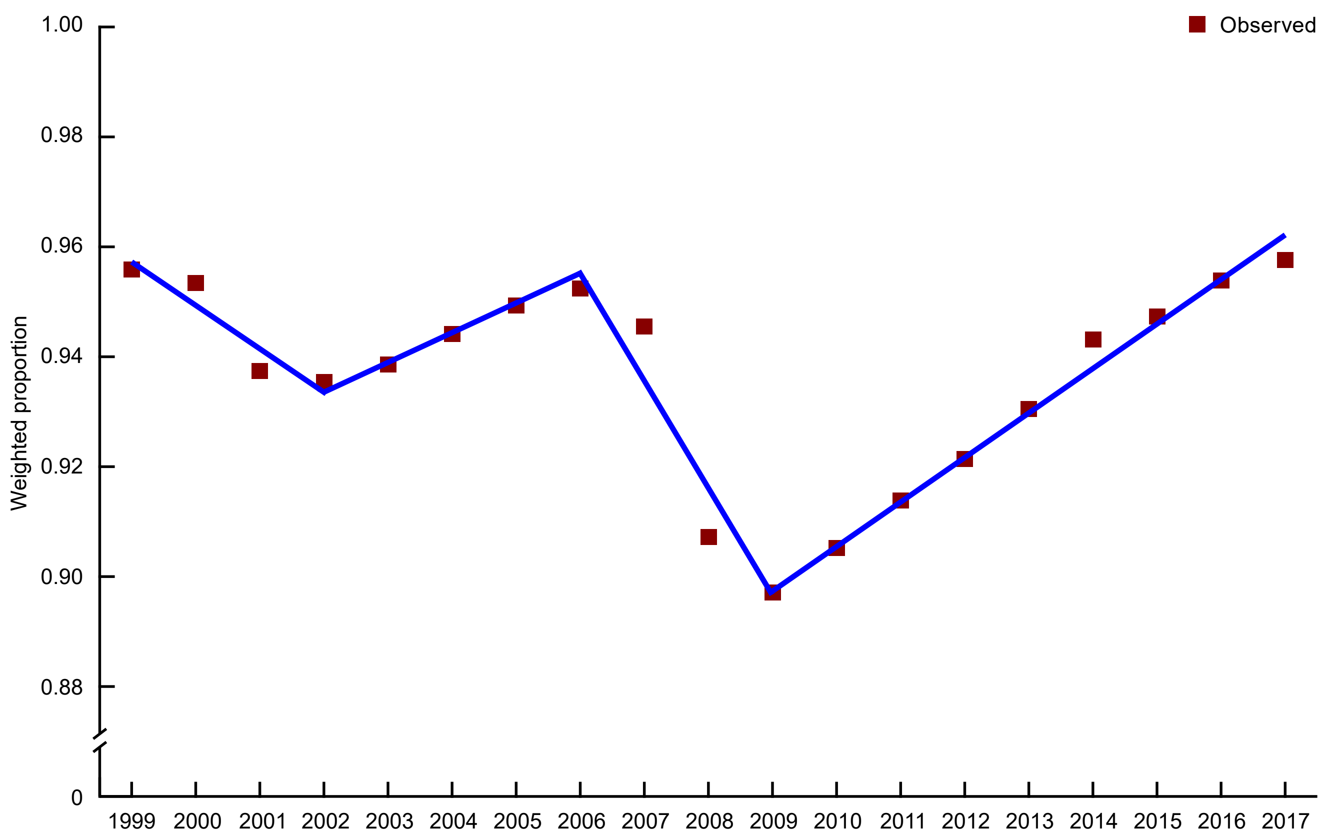
Table V. Final piecewise regression estimates with standard errors for the employment rate among people age 16 and older in the U.S. labor force

Model components	β	Standard error	p value
Intercept	0.96	0.0008	< 0.0001
1st line segment (1999–2002)	-0.01	0.0004	< 0.0001
2nd line segment (2002–2006)	0.01	0.0002	< 0.0001
3rd line segment (2006–2009)	-0.02	0.0003	< 0.0001
4th line segment (2009–2017)	0.01	0.0001	< 0.0001
Change in slopes (1 versus 2)	0.01	0.0005	< 0.0001
Change in slopes (2 versus 3)	-0.02	0.0005	< 0.0001
Change in slopes (3 versus 4)	0.03	0.0004	< 0.0001

NOTES: People are considered employed if they are employed during the survey week. Labor force includes people who have a job and people who are jobless, looking for a job, and available for work.

SOURCE: U.S. Census Bureau, Current Population Survey Annual Social and Economic Supplement, 1999–2017.

Figure VII. Final piecewise regression model for the employment rate among people age 16 and older in the U.S. labor force



NOTES: People are considered employed if they are employed during the survey week. Labor force includes people who have a job and people who are jobless, looking for a job, and available for work. Piecewise regression model shown is presented in Table V in this report.
SOURCE: U.S. Census Bureau, Current Population Survey Annual Social and Economic Supplement, 1999–2017.

Example C. Age-adjusted Body Mass Index Among Mexican-American Women Age 20 and Older: National Health and Nutrition Examination Survey, 1999–2016

Overview

This example demonstrates a case in which the test for a linear trend using SUDAAN is statistically significant, the test for a quadratic trend using SUDAAN is not statistically significant, the Joinpoint software suggests one joinpoint at the 2009–2010 survey cycle, and a piecewise regression in SUDAAN indicates that the change in the slopes between the two line segments around the 2009–2010 time point is statistically significant. In this case, the perceived inconsistency between step 2 and steps 3–4 are due to differences between modeling a nonlinear polynomial (quadratic) curve and modeling two linear line segments in a piecewise regression model.

Step 1: Compute estimates for each survey cycle and plot the estimates

Weighted estimates and standard errors by survey cycle are presented in Table VI and Figure VIII.

Step 2: Initial assessment of nonlinearity: Polynomial regression or orthogonal polynomial contrasts

Estimates with standard errors are presented in Table VII for the simple linear regression model and quadratic regression model.

Step 3: Estimate the number and location of joinpoints for nonlinear trends using Joinpoint software

For this example, the following options were selected in the Joinpoint software:

1. Log transformation: No
2. Heteroscedastic/correlated errors option: Variance–covariance matrix (provided)
3. Method: Grid search
   a. Minimum number of observations from a joinpoint to either end of the data: Two
   b. Minimum number of observations between two joinpoints: Two
   c. Number of points to place between adjacent observed *x* values in the grid search: Zero
4. Number of joinpoints:
   a. Minimum: Zero
   b. Maximum: One
5. Model selection method: BIC (fewer than 10 time points).

Automated output from the Joinpoint software (graph and model estimates) are presented in Figure IX.

Step 4: Obtain final slope estimates and tests of trend using a standard survey package

Because the Joinpoint software identifies a joinpoint at the 2009–2010 survey cycle (the sixth time point), a piecewise regression model was run in SUDAAN. This model also identified a statistically significant change in slopes at the 2009–2010 survey cycle. As a result, the piecewise regression model was chosen as the final model (Table VIII).

Table VI. Age-adjusted mean body mass index with standard errors, by survey cycle among Mexican-American women age 20 and older

Survey cycle	*n*	Mean (weighted)	Standard error
1999–2000	572	29.0	0.4
2001–2002	450	29.1	0.5
2003–2004	415	29.8	0.5
2005–2006	402	29.5	0.4
2007–2008	486	29.9	0.3
2009–2010	547	29.9	0.2
2011–2012	237	30.6	0.5
2013–2014	375	31.2	0.4
2015–2016	498	31.9	0.4

NOTES: Body mass index (BMI) is calculated as weight in kilograms divided by height in meters squared (kg/m^2). Age-adjusted mean BMI was obtained using record-level data and SUDAAN's PROC DESCRIPT with mobile examination center weights and direct age adjustment to the U.S. Census Bureau standard female population.

SOURCE: National Center for Health Statistics, National Health and Nutrition Examination Survey, 1999–2016.

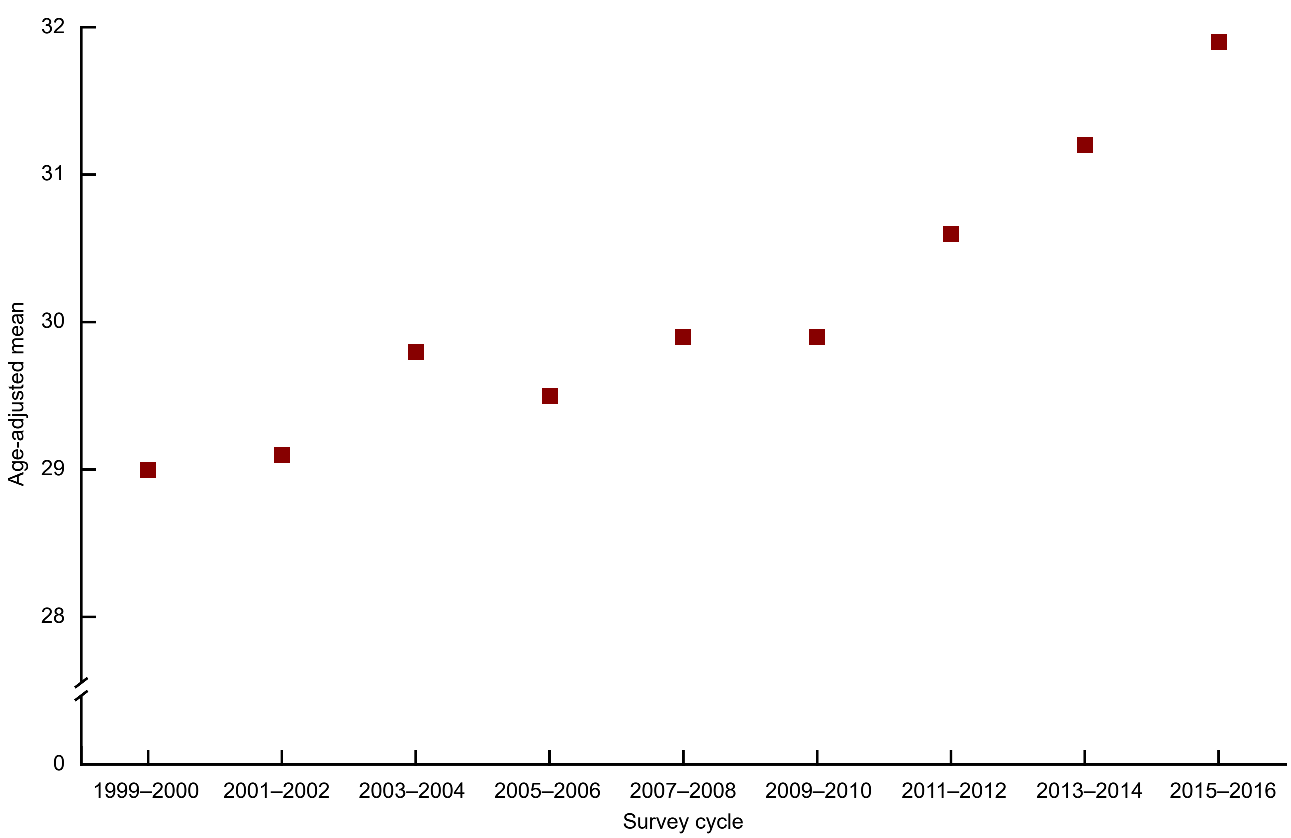
Conclusions

Based on SUDAAN, the change in slopes for the piecewise model suggested by the Joinpoint software (with a joinpoint at the 2009–2010 survey cycle) is statistically significant (p = 0.02) (Table VIII). This coincides with the graphical depictions and subject matter expertise. Therefore, the best model for the data is the piecewise regression model (Figure X) indicating that age-adjusted mean body mass index among Mexican-American females increased at an average rate of 0.18 per survey cycle (about 0.09 per year) between 1999–2000 and 2009–2010 and at an average rate of 0.65 per survey cycle (about 0.32 per year) between 2009–2010 and 2017–2018.

Explanation of differences

In this case, the results from the linear and quadratic regressions in step 2 indicate a linear trend (Table VII), the results from the Joinpoint software suggest using a piecewise model (Figure IX), and the piecewise regression model in SUDAAN is statistically significant (Table VIII, Figure X). The perceived inconsistency between step 1 (statistically insignificant quadratic regression) and steps 3 and 4 (statistically significant piecewise regressions) are due to differences between modeling a nonlinear polynomial (quadratic) curve and modeling two linear line segments in a piecewise regression model.

Figure VIII. Age-adjusted mean body mass index among Mexican-American women age 20 and older



NOTES: Body mass index (BMI) is calculated as weight in kilograms divided by height in meters squared (kg/m^2). Age-adjusted mean BMI was obtained using record-level data and SUDAAN's PROC DESCRIPT with mobile examination center weights and direct age-adjustment to the U.S. Census standard female population.
SOURCE: National Center for Health Statistics, National Health and Nutrition Examination Survey, 1999–2016.

Table VII. Linear and quadration regression estimates with standard errors of age-adjusted mean body mass index among Mexican-American women age 20 and older

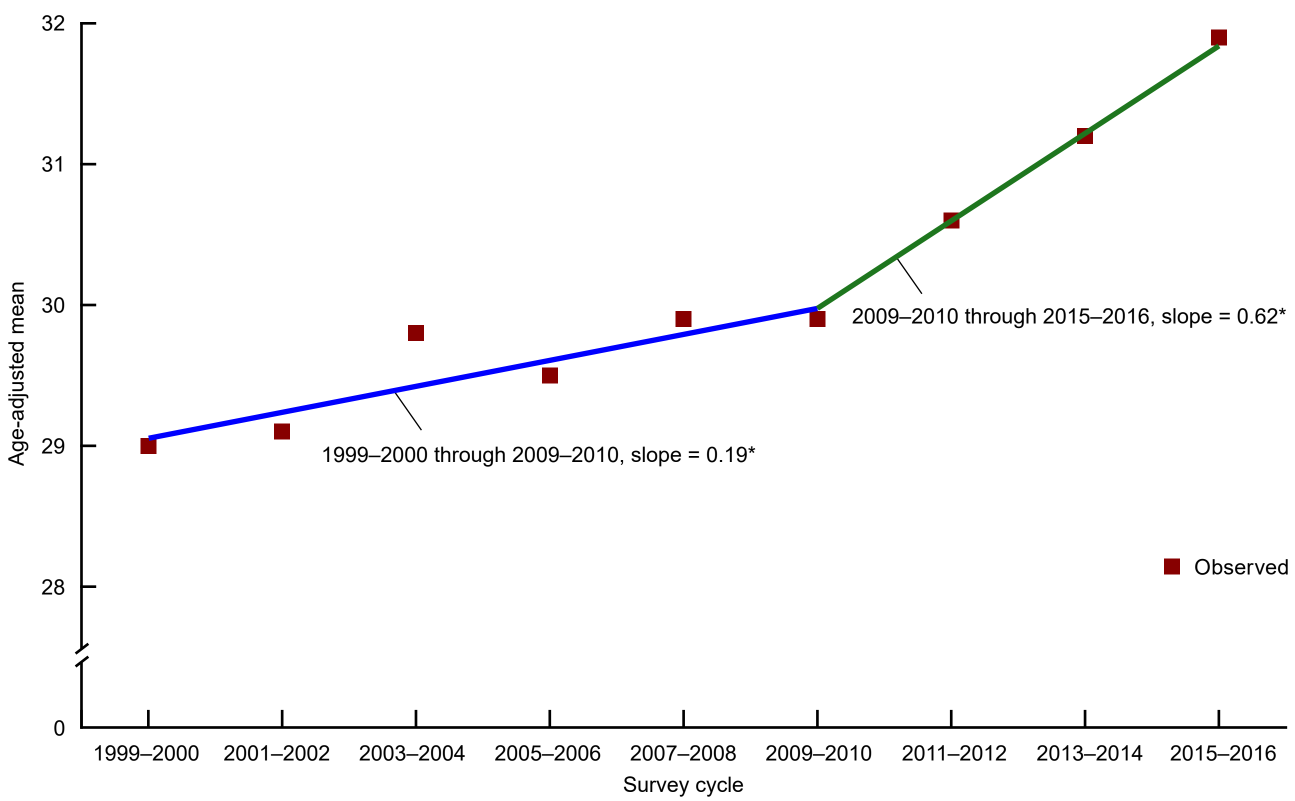
Model	β_0 (standard error)	β_1 (standard error) Age	β_2 (standard error) Survey cycle	β_3 (standard error) Survey cycle squared	Linear and quadratic contrast
Simple linear regression	26.90 (0.42)	0.77 (0.14)	0.35 (0.06)	…	…
p values	< 0.0001	< 0.0001	< 0.0001	…	< 0.0001
Quadratic regression	27.73 (0.61)	0.77 (0.13)	-0.06 (0.23)	0.04 (0.02)	…
p values	< 0.0001	< 0.0001	0.7830	0.0732	0.0824

… Category not applicable.

NOTES: Body mass index (BMI) is calculated as weight in kilograms divided by height in meters squared (kg/m^2). Mean BMI estimates and standard errors were obtained using record-level data and SUDAAN's PROC REGRESS with mobile examination center weights. Survey cycles 1999–2000 through 2015–2016 were coded as 1 through 9 for all regression analyses.

SOURCE: National Center for Health Statistics, National Health and Nutrition Examination Survey, 1999–2016.

Figure IX. Joinpoint software's automated output: Age-adjusted mean body mass index among Mexican-American women age 20 and older



* Indicates that the slope is significantly different from zero at the α = 0.05 level. Final selected model has one joinpoint.
NOTES: Body mass index (BMI) is calculated as weight in kilograms divided by height in meters squared (kg/m^2). Age-adjusted mean BMI was obtained using record-level data and SUDAAN's PROC DESCRIPT with mobile examination center weights and direct age-adjustment to the U.S. Census standard female population. Survey cycles 1999–2000 through 2015–2016 were coded as 1 through 9 for all regression analyses.
SOURCE: National Center for Health Statistics, National Health and Nutrition Examination Survey, 1999–2016.

Model	Number of joinpoints	Number of observations	Number of parameters	Degrees of freedom	Sum of squared errors	BIC
1.	0 joinpoint(s)	9	2	7	8.0725392	0.3795156
2.	1 joinpoint(s)	9	4	5	1.2228318	-1.019511

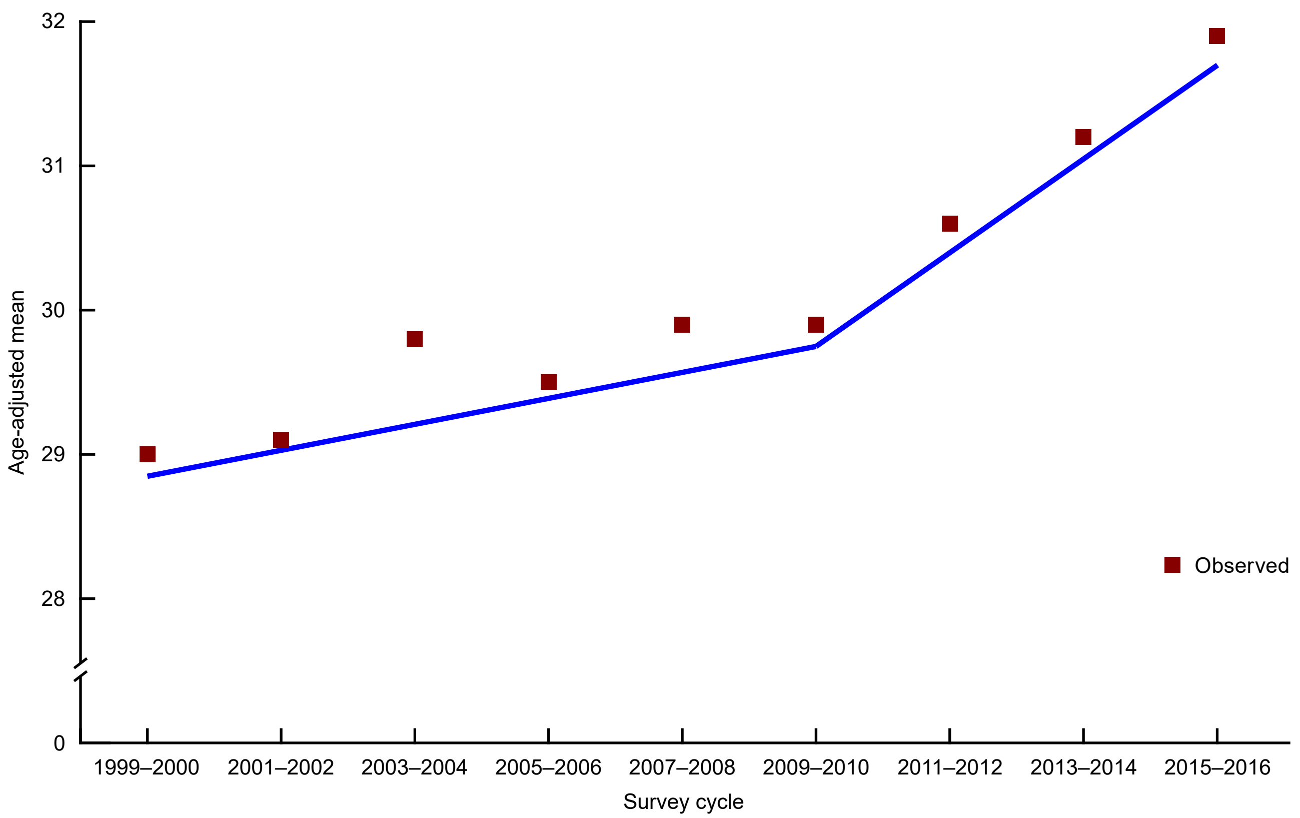
Table VIII. Final piecewise regression estimates with standard errors of age-adjusted mean body mass index among Mexican-American women age 20 and older

Model components	β (standard error)	p value
Intercept	28.67 (0.43)	< 0.0001
1st line segment (1999–2000 through 2009–2010)	0.18 (0.09)	0.05
2nd line segment (2009–2010 through 2017–2018)	0.65 (0.15)	< 0.0001
Change in slopes	0.47 (0.20)	0.02

NOTES: Body mass index (BMI) is calculated as weight in kilograms divided by height in meters squared (kg/m^2). Mean BMI estimates and standard errors were obtained using record-level data and SUDAAN's PROC REGRESS with age-adjusted mobile examination center weights. Survey cycles 1999–2000 through 2015–2016 were coded as 1 through 9 for all regression analyses.

SOURCE: National Center for Health Statistics, National Health and Nutrition Examination Survey, 1999–2016.

Figure X. Final piecewise regression model for age-adjusted body mass index among Mexican-American women ages 20 and older



NOTES: Body mass index (BMI) is calculated as weight in kilograms divided by height in meters squared (kg/m^2). Mean BMI estimates and standard errors for the regression were obtained using record-level data and SUDAAN's PROC REGRESS with age-adjusted mobile examination center weights. Survey cycles 1999–2000 through 2015–2016 were coded as 1 through 9 for all regression analyses. Piecewise regression model shown is presented in Table VIII in this report.
SOURCE: National Center for Health Statistics, National Health and Nutrition Examination Survey, 1999–2016.

Example D. Percentage of U.S. Children Age 17 and Younger Who Had Private Health Insurance at the Time of Interview: National Health Interview Survey, 2007–2018

Overview

This example demonstrates a case in which the tests for quadratic and cubic trends are both statistically significant and Joinpoint software suggests two joinpoints (2010 and 2013). However, when the piecewise regression model suggested by the Joinpoint software is fit in the R survey package, the change in slopes between segments two and three (at 2013) is not statistically significant. A piecewise regression in the R survey package with a single joinpoint at 2010 indicates a good fit and is chosen as the best model for the data. Data used in this example are from the IPUMS Health Surveys: National Health Interview Series (19).

Step 1: Compute annual survey estimates and plot the estimates

Weighted percentage estimates and standard errors by survey cycle are presented in Table IX and Figure XI.

Step 2: Initial assessment of nonlinearity: Polynomial regression or orthogonal polynomial contrasts

Estimates with standard errors are presented in Table X for the simple linear regression model, quadratic regression model, and cubic regression model.

Step 3: Estimate the number and location of joinpoints for nonlinear trends using Joinpoint software

For this example, the following options were selected in the Joinpoint software:

1. Log transformation: No
2. Heteroscedastic/correlated errors option: Variance–covariance matrix (provided)
3. Method: Grid search
    a. Minimum number of observations from a joinpoint to either end of the data: Two
    b. Minimum number of observations between two joinpoints: Two
    c. Number of points to place between adjacent observed *x* values in the grid search: Zero
4. Number of joinpoints:
    a. Minimum: Zero
    b. Maximum: Two
5. Model selection method: Permutation test (10 or more time points).

Automated output from the Joinpoint software (graph and model estimates) are presented in Figure XII.

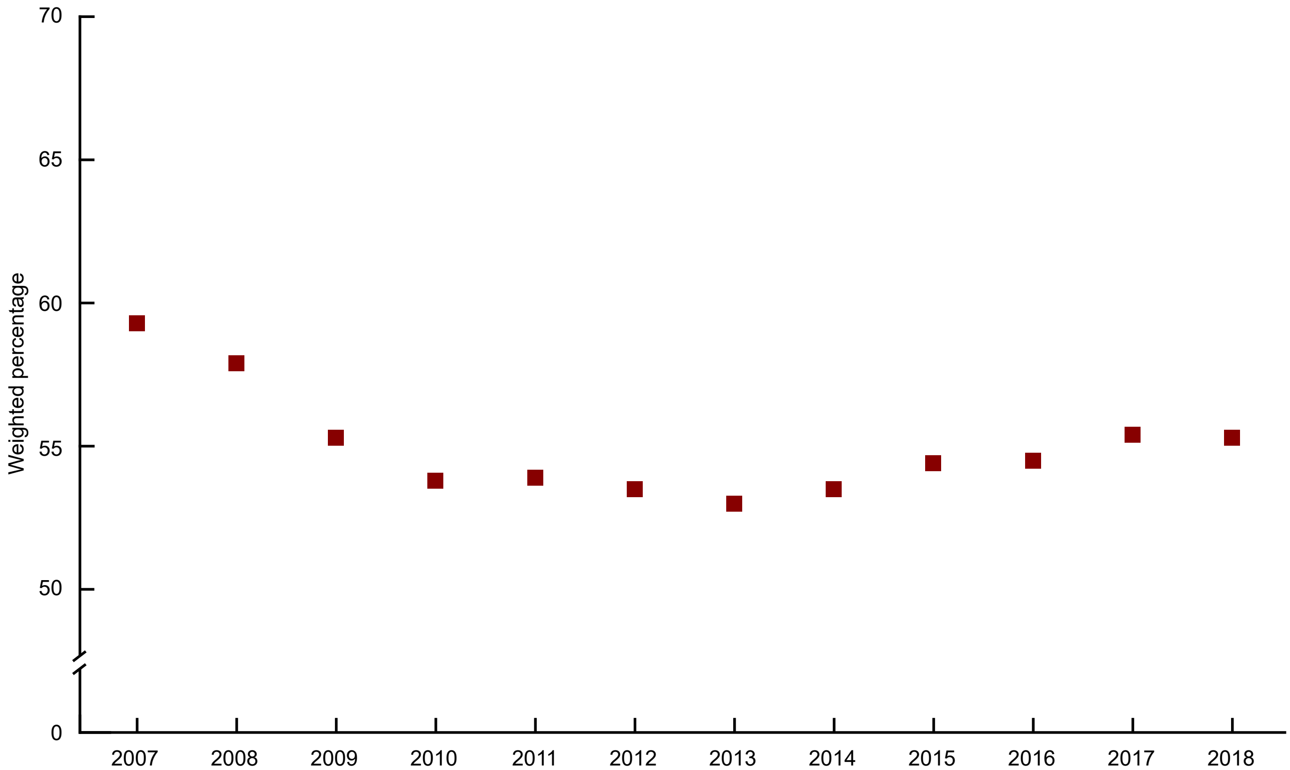
Table IX. Survey estimates and standard errors by year for the percentage of U.S. children age 17 and younger who had private health insurance at the time of interview

Year	*n*	Weighted percent	Standard error
2007	9,373	59.3	0.75
2008	8,766	57.9	0.77
2009	11,116	55.3	0.81
2010	11,243	53.8	0.76
2011	12,793	53.9	0.71
2012	13,210	53.5	0.71
2013	12,808	53.0	0.67
2014	13,325	53.5	0.69
2015	12,233	54.4	0.72
2016	11,049	54.5	0.76
2017	8,794	55.4	0.85
2018	8,234	55.3	0.91

NOTES: Children were defined as having private health insurance if Children were defined by a private health insurance plan, defined as insurance other than Medicare, Medicaid, state Children's Health Insurance Plan (CHIP), state-sponsored health plans, other government programs, and military health plans (including TRICARE, VA, and Civilian Health and Medical Program of VA [CHAMP-VA]). These plans include those obtained through an employer, purchased directly, purchased through local or community programs, or purchased through the Health Insurance Marketplace or a state-based exchange. Private coverage excludes plans that pay for only one type of service, such as dental, vision, or prescription drugs.

SOURCE: National Center for Health Statistics, IPUMS Health Surveys, National Health Interview Survey, Family Core component version 7.3, 2007–2018.

Figure XI. Percentage of U.S. children age 17 and younger who had private health insurance at the time of interview



NOTES: Children were defined as having private health insurance if they had health insurance coverage and were covered by a private health insurance plan, defined as insurance other than Medicare, Medicaid, State Children's Health Insurance Plan (CHIP), state-sponsored health plans, other government programs, and military health plans (including TRICARE, VA, and Civilian Health and Medical Program of VA [CHAMP-VA]). These plans include those obtained through an employer, purchased directly, purchased through local or community programs, or purchased through the Health Insurance Marketplace or a state-based exchange. Private coverage excludes plans that pay for only one type of service, such as dental, vision, or prescription drugs.
SOURCE: National Center for Health Statistics, IPUMS Health Surveys, National Health Interview Survey, Family Core component version 7.3, 2007–2018.

Table X. Linear, quadratic, and cubic regression estimates with standard errors for the percentage of U.S. children age 17 and younger who had private health insurance at the time of interview

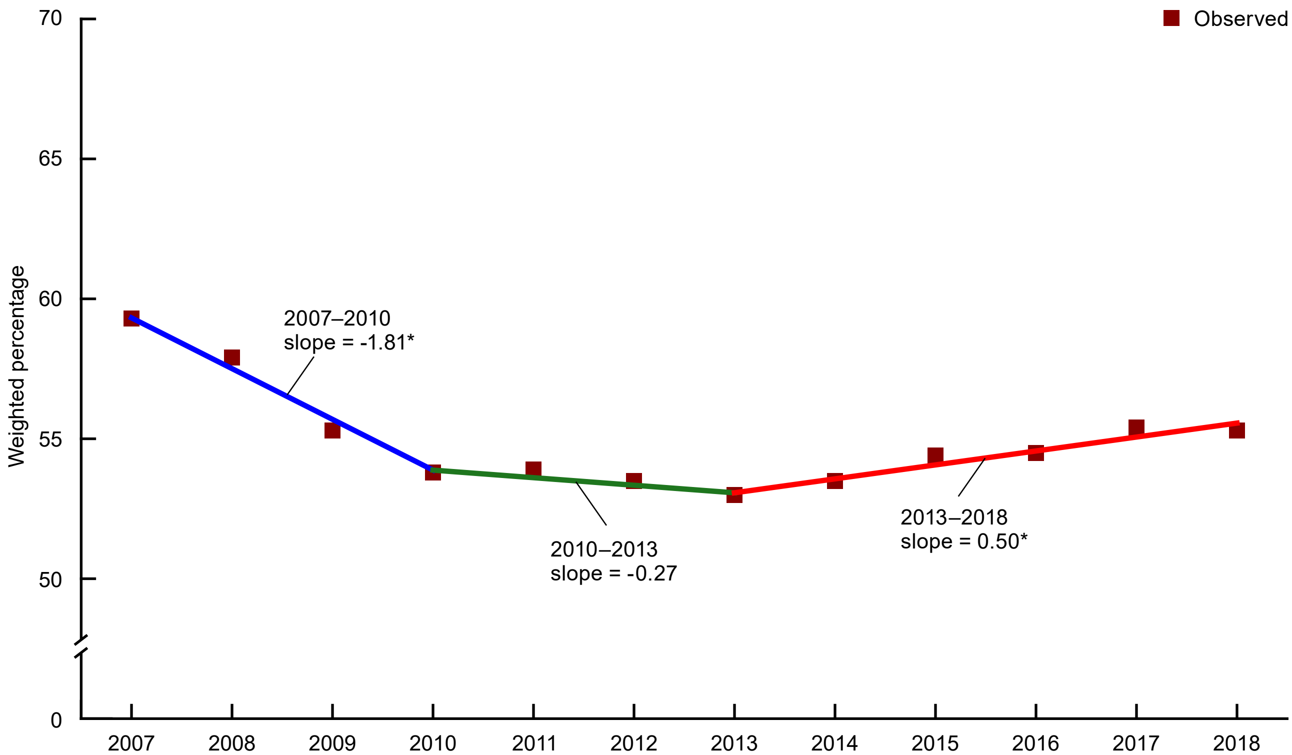
Model	β_0 (standard error)	β_1 (standard error)	β_2 (standard error)	β_3 (standard error)
	Intercept	Year	Year squared	Year cubed
Linear regression	56.35	-0.25	…	…
p values	< 0.0001	0.0030	…	…
Quadratic regression	58.93	-1.80	0.14	…
p values	< 0.0001	< 0.0001	< 0.0001	…
Cubic regression	59.65	-2.81	0.38	-0.01
p values	< 0.0001	< 0.0001	0.0006	0.0277

… Category not applicable.

NOTES: Children were defined as having private health insurance if they had health insurance coverage and were covered by a private health insurance plan, defined as insurance other than Medicare, Medicaid, state Children’s Health Insurance Plan (CHIP), state-sponsored health plans, other government programs, and military health plans (including TRICARE, VA, and Civilian Health and Medical Program of VA [CHAMP-VA]). These plans include those obtained through an employer, purchased directly, purchased through local or community programs, or purchased through the Health Insurance Marketplace or a state-based exchange. Private coverage excludes plans that pay for only one type of service, such as dental, vision, or prescription drugs. The year variable was centered at 2007 (YEAR minus 2007) before running the polynomial regression.

SOURCE: National Center for Health Statistics, IPUMS Health Surveys, National Health Interview Survey, Family Core component version 7.3, 2007–2018.

Figure XII. Joinpoint software's automated output: Percentage of U.S. children age 17 and younger who had private health insurance at the time of interview



* Indicates that the slope is significantly different from zero at the α = 0.05 level. Final selected model has two joinpoints.
NOTES: Children were defined as having private health insurance if they had health insurance coverage and were covered by a private health insurance plan, defined as insurance other than Medicare, Medicaid, State Children's Health Insurance Plan (CHIP), state-sponsored health plans, other government programs, and military health plans (including TRICARE, VA, and Civilian Health and Medical Program of VA [CHAMP-VA]). These plans include those obtained through an employer, purchased directly, purchased through local or community programs, or purchased through the Health Insurance Marketplace or a state-based exchange. Private coverage excludes plans that pay for only one type of service, such as dental, vision, or prescription drugs.
SOURCE: National Center for Health Statistics, IPUMS Health Surveys, National Health Interview Survey, Family Core component version 7.3, 2007–2018.

Test number	Null hypothesis	Alternate hypothesis	Degrees of freedom		Number of permutations	*p* value	Significance level
			Numerator	Denominator			
1	0 joinpoint(s)	2 joinpoint(s)	4	6	4500	0.0002222	0.025
2	1 joinpoint(s)	2 joinpoint(s)	2	6	4500	0.0031111	0.050

Step 4: Obtain final slope estimates and tests of trend using a standard survey package

Estimates with standard errors for the prespecified piecewise regression model recommended by the Joinpoint software and estimated using the R survey package are presented in Table XI. Estimates with standard errors for the final piecewise regression model estimated using the R survey package are presented in Table XII and Figure XIII.

Conclusions

Based on the R survey package, the change in slopes at 2010 (p = 0.0006) is statistically significant, while the change in slopes at 2013 (as suggested by the Joinpoint software) is not statistically significant (p = 0.0847). As a result, the best model for the data is the piecewise regression model (Table XII, Figure XIII) indicating that the percentage of U.S. children age 17 and younger who had private health insurance at the time of the interview decreased at an average rate of 2.11% (p < 0.0001) per year between 2007 and 2010 and then remained relatively steady between 2010 and 2018.

Explanation of differences

In this example, the tests for quadratic and cubic trends are both statistically significant (Table X) and the Joinpoint software suggests two joinpoints (2010 and 2013, Figure XII). However, when the piecewise regression model suggested by the Joinpoint software is fit in the R survey package, the change in slopes between segments two and three (at 2013) is not statistically significant (Table XI). In this case, the inconsistency between steps 1–3 and step 4 are likely due to differences in the model selection criterion for the BIC test (the Joinpoint software) versus the segment-wise *t* test (R survey package); BIC uses the entire time series, while the segment-wise testing uses only segment-specific observations.

Table XI. Model recommended by Joinpoint software: Piecewise regression estimates with standard errors for the percentage of U.S. children age 17 or younger who had private health insurance at the time of interview

Model component	β (standard error)	p value
Intercept	59.42 (0.69)	< 0.0001
1st line segment (2007–2010)	-1.86 (0.30)	< 0.0001
2nd line segment (2010–2013)	-0.21 (0.24)	0.3760
3rd line segment (2013–2018)	0.47 (0.22)	0.0349
Change in slopes (1st line segment to 2nd line segment)	1.65 (0.48)	0.0006
Change in slopes (2nd line segment to 3rd line segment)	0.68 (0.39)	0.0847

NOTES: Children were defined as having private health insurance if they had health insurance coverage and were covered by a private health insurance plan, defined as insurance other than Medicare, Medicaid, state Children's Health Insurance Plan (CHIP), state-sponsored health plans, other government programs, and military health plans (including TRICARE, VA, and Civilian Health and Medical Program of VA [CHAMP-VA]). These plans include those obtained through an employer, purchased directly, purchased through local or community programs, or purchased through the Health Insurance Marketplace or a state-based exchange. Private coverage excludes plans that pay for only one type of service, such as dental, vision, or prescription drugs. The year variable was centered at 2007 (YEAR minus 2007) before running the piecewise regression.

SOURCE: National Center for Health Statistics, IPUMS Health Surveys, National Health Interview Survey, Family Core component version 7.3, 2007–2018.

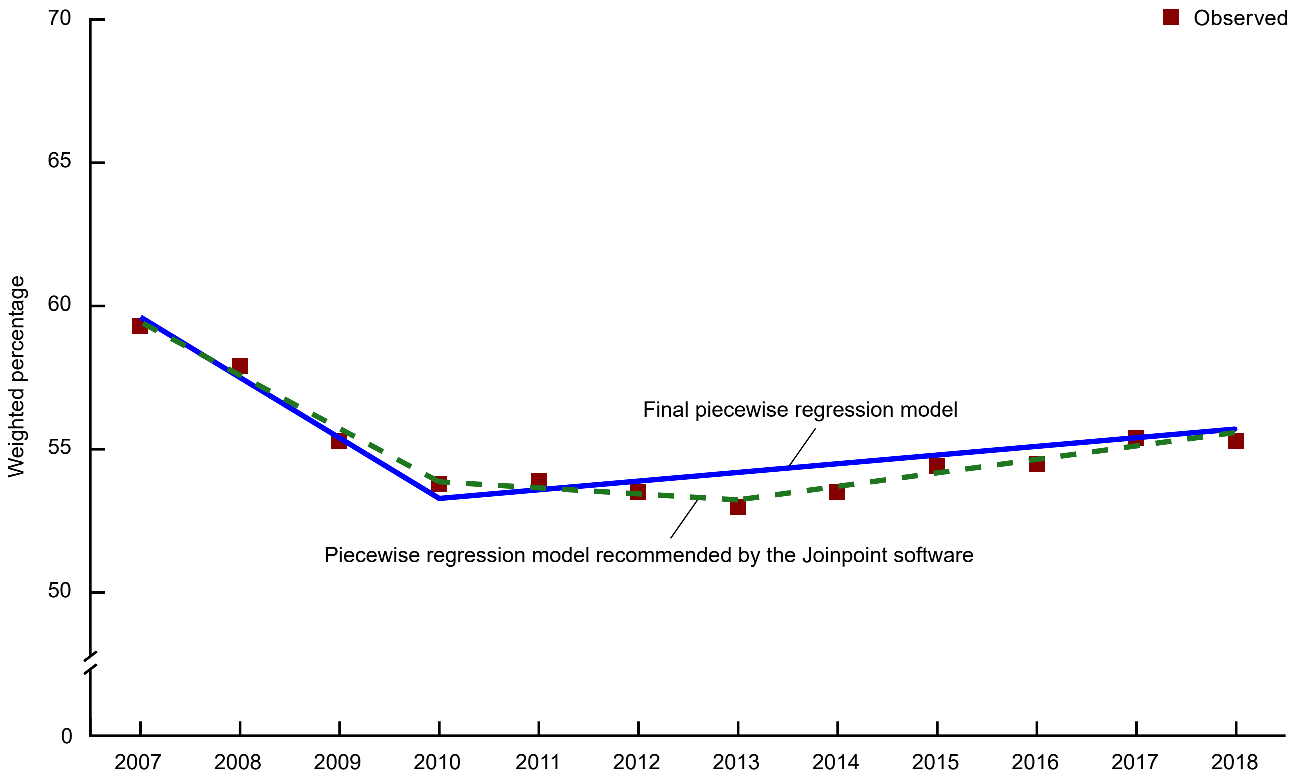
Table XII. Final model: Piecewise regression estimates with standard errors for the percentage of U.S. children age 17 or younger who had private insurance at the time of interview

Component	β (standard error)	p value
Intercept	59.59 (0.68)	< 0.0001
1st line segment (2007–2010)	-2.11 (0.29)	< 0.0001
2nd line segment (2010–2018)	0.22 (0.13)	0.0816
Change in slopes (1st line segment to 2nd line segment)	2.33 (0.37)	< 0.0001

NOTES: Children were defined as having private health insurance if they had health insurance coverage and were covered by a private health insurance plan, defined as insurance other than Medicare, Medicaid, state Children's Health Insurance Plan (CHIP), state-sponsored health plans, other government programs, and military health plans (including TRICARE, VA, and Civilian Health and Medical Program of VA [CHAMP-VA]). These plans include those obtained through an employer, purchased directly, purchased through local or community programs, or purchased through the Health Insurance Marketplace or a state-based exchange. Private coverage excludes plans that pay for only one type of service, such as dental, vision, or prescription drugs. The year variable was centered at 2007 (YEAR minus 2007) before running the piecewise regression.

SOURCE: National Center for Health Statistics, IPUMS Health Surveys, National Health Interview Survey, Family Core component version 7.3, 2007–2018.

Figure XIII. Final piecewise regression model for the percentage of U.S. children age 17 and younger who had private health insurance at the time of interview compared with the piecewise regression model recommended by the Joinpoint software



NOTES: Children were defined as having private health insurance if they had health insurance coverage and were covered by a private health insurance plan, defined as insurance other than Medicare, Medicaid, State Children's Health Insurance Plan (CHIP), state-sponsored health plans, other government programs, and military health plans (including TRICARE, VA, and Civilian Health and Medical Program of VA [CHAMP-VA]). These plans include those obtained through an employer, purchased directly, purchased through local or community programs, or purchased through the Health Insurance Marketplace or a state-based exchange. Private coverage excludes plans that pay for only one type of service, such as dental, vision, or prescription drugs. Piecewise regression models shown are presented in Tables XI and XII in this report. The year variable was centered at 2007 (YEAR-2007) before running the piecewise regression analyses.
SOURCE: National Center for Health Statistics, IPUMS Health Surveys, National Health Interview Survey, Family Core component version 7.3, 2007–2018.

Appendix II: Transforming the Variance–covariance Matrix of Proportions to the Log-odds Scale

As described in Issues 8 and 12 and demonstrated in Example B and Appendix VI of the “National Center for Health Statistics Guidelines for Analysis of Trends,” logistic regression is often used to model a time trend for survey data when the outcome variable is binary (1). If the trend is nonlinear and the National Cancer Institute Joinpoint Regression Software is used to identify the number and location of joinpoints, it is preferable to transform the proportions and standard errors to the log-odds scale before inputting to the Joinpoint software.

This transformation can be achieved as identified in Appendix VI of the “National Center for Health Statistics Guidelines for Analysis of Trends” and as described on page 32 of Cox’s *The Analysis of Binary Data* (23):

1. Transform the original proportion, $\hat{p}$, as follows:

$$\ln\left(\frac{\hat{p}}{1-\hat{p}}\right)$$

2. Transform the original estimated standard error, $se(\hat{p})$, as follows:

$$\frac{\widehat{se}(\hat{p})}{\hat{p}(1-\hat{p})}$$

Here, the covariance of P_i and P_{i+1} is transformed to the log-odds (logit) scale. This can be used by the analyst to transform the original variance–covariance matrix for a series of n estimated proportions $\hat{p}_i$, $\hat{p}_{i+1}$, ..., $\hat{p}_{i+(n-1)}$ collected at time points i through $\{i+(n-1)\}$ into a variance–covariance matrix for

$$\ln\left(\frac{\hat{p}_1}{1-\hat{p}_1}\right), \ln\left(\frac{\hat{p}_2}{1-\hat{p}_2}\right), \ldots, \ln\left(\frac{\hat{p}_{i+(n-1)}}{1-\hat{p}_{i+(n-1)}}\right)$$

For clarity, let $P_i = X$ and $P_{i+1} = Y$. Let X be collected at time point i, and Y at time point $i+1$. Then $X \sim (\mu_X, Var(X))$ and $Y \sim (\mu_Y, Var(Y))$, where μ_X and μ_Y are proportions. Define

$$g(x) = logit(x) = ln\left(\frac{x}{1-x}\right),\ g(y) = logit(y) = ln\left(\frac{y}{1-y}\right)$$

$U = g(X)$, and $V = g(Y)$. The goal is to obtain the covariance of U and V.

By definition, $Cov(U,V) = E(UV) - E(U)E(V)$
$= E[g(X)g(Y)] - E[g(X)]E[g(Y)]$

Using the first-order Taylor series expansions of $g(X)$ and $g(Y)$ around the expected values $E[X]$ and $E[Y]$, respectively,

$$Cov(U,V) \approx E[(g(E(X)) + g'(E(X)) \bullet (X - E(X))) \bullet (g(E(Y)) + g'(E(Y)) \bullet (Y - E(Y)))] - E[g(X)] \bullet E[g(Y)]$$

$$Cov(U,V) \approx E[g(E(X)) \bullet g(E(Y)) + g(E(X)) \bullet g'(E(Y)) \bullet (Y - E(Y)) + g(E(Y)) \bullet g'(E(X)) \bullet (X - E(X)) + g'(E(X)) \bullet g'(E(Y)) \bullet (X - E(X)) \bullet (Y - E(Y))] - E[g(X)] \bullet E[g(Y)]$$

$$Cov(U,V) \approx E[(g(E(X)) \bullet g(E(Y))] + E[g(E(X)) \bullet g'(E(Y)) \bullet (Y - E(Y))] + E[g(E(Y)) \bullet g'(E(X)) \bullet (X - E(X))] + E[g'(E(X)) \bullet g'(E(Y)) \bullet (X - E(X)) \bullet (Y - E(Y))] - E[g(X)] \bullet E[g(Y)]$$

Recall that:

$$E[g(E(X)) \bullet g'(E(Y)) \bullet (Y - E(Y))] = c_1 \bullet c_2 \bullet E[Y - E(Y)] = 0$$

where c_1 and c_2 are constants,

$$E[g(E(Y)) \bullet g'(E(X)) \bullet (X - E(X))] = c_3 \bullet c_4 \bullet E[X - E(X)] = 0$$

where c_3 and c_4 are constants, and

$$E[(X - E(X)) \bullet (Y - E(Y))] = Cov(X,Y)$$

Thus,

$$Cov(U,V) \approx g(E(X)) \bullet g(E(Y)) + g'(E(X)) \bullet g'(E(Y)) \bullet Cov(X,Y) - E(g(X)) \bullet E(g(Y))$$

From the first-order Taylor series expansions of $g(X)$ and $g(Y)$, shown previously, their expected values are $E[g(X)] \approx g[E(X)]$ and $E[g(Y)] \approx g[E(Y)]$. Therefore,

$$Cov(U,V) \approx g'(E(X)) \bullet g'(E(Y)) \bullet Cov(X,Y)$$

Finally, because

$$g'(x) = \frac{1}{x \bullet (1-x)} \text{ and } g'(y) = \frac{1}{y \bullet (1-y)}$$

it follows that

$$Cov(U,V) \approx \frac{Cov(X,Y)}{E(X) \bullet (1-E(X)) \bullet E(Y) \bullet (1-E(Y))}$$

Hence, an estimate for the covariance of the logit(P_i) and logit(P_{i+1}) is:

$$Cov[\log it(P_i), \log it(P_{i+1})] \approx \frac{Cov(\hat{p}_i, \hat{p}_{i+1})}{(\hat{p}_i) \bullet (1-\hat{p}_i) \bullet (\hat{p}_{i+1}) \bullet (1-\hat{p}_{i+1})}$$

Appendix III: Implementing the Transformation of the Variance–covariance Matrix of Proportions to the Log-odds Scale Using SUDAAN and SAS

Step 1: Obtain Estimates Across Time Using SUDAAN PROC VARGEN

Estimates include percentages (*perc*), proportion of "successes" (*p*), proportion of "failures" (1 − *p*), and transformed prevalences (*logit p*). While not all estimates obtained by SUDAAN PROC VARGEN will be used to obtain the variance–covariance matrix, together the estimates provide a thorough overview of the overall trend. The data set must be sorted by the survey design variables (strata and psu) before obtaining the estimates.

```
proc sort data=<DATA SET>; by <STRATA VARIABLE> <PSU VARIABLE>; run;
proc vargen data=<DATA SET> design=<DESIGN OPTION>;
nest <STRATA VARIABLE> <PSU VARIABLE> / missunit;
subpopn <SUBGROUP OF INTEREST>;
weight <WEIGHT VARIABLE>;
class <TIMEPOINT VARIABLE>;
xper perc : <BINARY VARIABLE OF INTEREST> / value = <0 or 1: outcome of interest>
name = "Percent of …";
parameter p : perc/100 / name="Proportion of …";
parameter np: 1-p / name="Proportion of …";
parameter g : log(p/(1-p)) / name="Logit of p: g(x)";
output nsum estim seestim varestim / filename=<NEW DATA SET NAME> nsumFMT=F##.##
estimFMT=F##.## seestimFMT=F##.## varestimFMT=F##.## replace;
run;
```

Step 2: Obtain the Variance–covariance Matrix for Estimated Proportions Across Time Using SAS PROC SURVEYMEANS in SAS/STAT Survey Procedures

SAS PROC SURVEYMEANS produces estimates and standard errors for proportions (*p*) but does not include (1 – *p*).

```
proc surveymeans data=<DATA SET>;
cluster <PSU VARIABLE>;
strata <STRATA VARIABLE>;
weight <WEIGHT VARIABLE>;
var <BINARY VARIABLE OF INTEREST>;
domain <SUBGROUP OF INTEREST*TIMEPOINT VARIABLE> / dfadj cov;
ods output
      Domain=<DATA SET OF ESTIMATES>
      DomainMeanCov=<DATA SET OF VARIANCE-COVARIANCE ESTIMATES>;
run;
```

Step 3: Combine Estimated Proportions With Variance–covariance Data to Create a Final Data Set of the Untransformed Variance–covariance Matrix

Combine estimated proportions (*p*) from step 2 (DATA SET OF ESTIMATES: *time point, variable p*) with variance–covariance data set from step 2 (DATA SET OF VARIANCE–COVARIANCE ESTIMATES: *cov1, cov2, … covn*) to create a data set of the form shown below (Table XIII). A new variable (*np*) is defined to represent the complement of *p* at each time point. The time point variable serves as the id variable for merging and may be numbered as preferred by the analyst (examples: 1 through *n*, year, survey cycle). The time point variable is not used in step 4 (SAS PROC IML).

```
data <DATA SET OF ESTIMATES VERSION 2>; set <DATA SET OF ESTIMATES>; if <IDENTIFY
SUBGROUP OF INTEREST>;
np=1-mean;
rename mean=p;
drop DomainLabel LowerCLMean N StdErr UpperCLMean VarName <VARIABLES RELATED TO SUB-
GROUP OF INTEREST>;
run;
proc print data=<DATA SET OF ESTIMATES VERSION 2>; run;

data <DATA SET OF VARIANCE-COVARIANCE ESTIMATES VERSION 2>; set <DATA SET OF VARI-
ANCE-COVARIANCE ESTIMATES> (keep=<TIMEPOINT VARIABLE> <VARIABLES RELATED TO SUBGROUP
OF INTEREST> COV1-<COVN>); if <IDENTIFY SUBGROUP OF INTEREST>;
drop <VARIABLES RELATED TO SUBGROUP OF INTEREST>;
run;
proc print data=<DATA SET OF VARIANCE-COVARIANCE ESTIMATES VERSION 2>; run;

proc sort data=<DATA SET OF ESTIMATES VERSION 2>; by <TIMEPOINT VARIABLE>; run;
proc sort data=<DATA SET OF VARIANCE-COVARIANCE ESTIMATES VERSION 2>; by <TIMEPOINT
VARIABLE>; run;
data <FINAL DATA SET OF UNTRANSFORMED VARIANCE-COVARIANCE ESTIMATES>; merge <DATA
SET OF ESTIMATES VERSION 2> <DATA SET OF VARIANCE-COVARIANCE ESTIMATES VERSION 2>;
by <TIMEPOINT VARIABLE>; run;
proc print data=<FINAL DATA SET OF UNTRANSFORMED VARIANCE-COVARIANCE ESTIMATES>;
run;
```

Example output from the final PROC PRINT is provided in Table XIII.

Table XIII. Example output for Step 3

TIMEPT	P	NP	COV1	COV2	COV3	…	COVN
1.	0.##	1-*p*	0.##	0.##	0.##	…	0.##
2.	0.##	1-*p*	0.##	0.##	0.##	…	0.##
3.	0.##	1-*p*	0.##	0.##	0.##	…	0.##
4.	0.##	1-*p*	0.##	0.##	0.##	…	0.##
5.	0.##	1-*p*	0.##	0.##	0.##	…	0.##
6.	0.##	1-*p*	0.##	0.##	0.##	…	0.##
7.	0.##	1-*p*	0.##	0.##	0.##	…	0.##
8.	0.##	1-*p*	0.##	0.##	0.##	…	0.##
9.	0.##	1-*p*	0.##	0.##	0.##	…	0.##
⋮	0.##	⋮	⋮	⋮	⋮	⋮	⋮
n.	0.##	1-*p*	0.##	0.##	0.##	…	0.##

SOURCE: National Center for Health Statistics.

Step 4: Use SAS PROC IML and the Data Set Created in Step 3 to Obtain the Transformed Variance–covariance Matrix

The transformed variance–covariance matrix is associated with the transformed estimates:

$$\ln\left(\frac{\hat{p}_1}{1-\hat{p}_1}\right), \ln\left(\frac{\hat{p}_2}{1-\hat{p}_2}\right), \ldots, \ln\left(\frac{\hat{p}_{i+(n-1)}}{1-\hat{p}_{i+(n-1)}}\right)$$

```
proc iml;
varNames = {"p" "np" "cov1" "cov2" "cov3" "cov4" "cov5" "cov6" "cov7" "cov8" "cov9"
... "cov<N>"};
use <FINAL DATA SET OF UNTRANSFORMED VARIANCE-COVARIANCE ESTIMATES>;
read all var varNames into j2;
close <FINAL DATA SET OF UNTRANSFORMED VARIANCE-COVARIANCE ESTIMATES>;
print j2[c=varNames];

<DATA SET OF TRANSFORMED VARIANCE-COVARIANCE ESTIMATES> = j(<N>,<N>,1);
do i=1 to <N>;
      do j=1 to <N>;
      <DATA SET OF TRANSFORMED VARIANCE-COVARIANCE ESTIMATES>[i,j]=j2[i,j+2]/
(j2[i,1]*j2[i,2]*j2[j,1]*j2[j,2]);
      end;
end;
print <DATA SET OF TRANSFORMED VARIANCE-COVARIANCE ESTIMATES>;
create <DATA SET OF TRANSFORMED VARIANCE-COVARIANCE ESTIMATES> from <DATA SET OF
TRANSFORMED VARIANCE-COVARIANCE ESTIMATES>;
append from <DATA SET OF TRANSFORMED VARIANCE-COVARIANCE ESTIMATES>;
show contents;
close <DATA SET OF TRANSFORMED VARIANCE-COVARIANCE ESTIMATES>;
print <DATA SET OF TRANSFORMED VARIANCE-COVARIANCE ESTIMATES>;

/*To save as a SAS data set*/
data <DATA SET OF TRANSFORMED VARIANCE-COVARIANCE ESTIMATES>; set <DATA SET OF
TRANSFORMED VARIANCE-COVARIANCE ESTIMATES>; run;
proc print data=<DATA SET OF TRANSFORMED VARIANCE-COVARIANCE ESTIMATES>; run;
```

Example output from the final PROC PRINT is provided in Table XIV.

Table XIV. Example output for Step 4

COL1	COL2	COL3	…	COLN
#.#	#.#	#.#	…	#.#
#.#	#.#	#.#	…	#.#
#.#	#.#	#.#	…	#.#
⋮	⋮	⋮	⋮	⋮
#.#	#.#	#.#	…	#.#

SOURCE: National Center for Health Statistics.

This variance–covariance matrix, transformed to the log-odds scale, can then be input into the National Cancer Institute's Joinpoint Regression Software under the correlated errors option to continue evaluating the trend by assessing the number and location of joinpoints. Note that column headers must be removed before reading the variance–covariance matrix into the Joinpoint software and that it is often advantageous to save the variance–covariance matrix as a CSV (comma-separated value) text file first.

Appendix IV: Example Transforming the Variance–covariance Matrix of Proportions to the Log-odds Scale Using SUDAAN and SAS

This example uses record-level data from the 2007–2018 National Health Interview Survey public-use person files to estimate trends in the percentage of U.S. adults ages 18–64 who were uninsured at the time of the interview. An adult was defined as uninsured if they did not have any private health insurance, Medicare, Medicaid, state Children's Health Insurance Program (CHIP), state-sponsored or other government-sponsored health plan, or military plan. An adult was also defined as uninsured if they had only Indian Health Service coverage or had only a private plan that paid for one type of service, such as accidents or dental care.

Data Preparation

```
libname a 'Pathname for accessing NHIS data' access=readonly;

data nhis; set a.nhis2007-a.nhis2018; run;

data nhis2; set nhis;
*Defining PSU and STRAT because combining survey years with different sample designs;
if 2007 le srvy_yr le 2015 then do;
      psu=psu_p;
      strat=strat_p+1000;
      end;
else if 2016 le srvy_yr le 2018 then do;
      psu=ppsu;
      strat=pstrat+2000;
      end;
*Defining NOINS using the NOTCOV variable to represent the uninsured;
if notcov in (7,8,9) then noins=.;
      else if notcov=2 then noins=0;
      else if notcov=1 then noins=1;
*Defining AGEGRP to identify the subpopulation (adults 18-64 years);
if 18 le age_p le 64 then agegrp=1;
      else agegrp=2;
run;

data nhis3; set nhis2 (keep=psu strat wtfa agegrp age_p srvy_yr notcov noins); run;
```

Step 1: Obtain Estimates Across Time Using SUDAAN PROC VARGEN

As suggested by the "National Center for Health Statistics Guidelines for Analysis of Trends," first compute annual survey estimates and plot the data (1). SUDAAN PROC VARGEN may be used to simultaneously obtain percentage estimates (*perc*), estimates for the proportion of "failures" (1 – *p*), and estimates of transformed log-odds (*logit p*) with standard errors. Not all estimates are used to obtain the variance–covariance matrix, but together provide a thorough overview of the overall trend. The data set must be sorted by the survey design variables (PSU and STRAT) before obtaining the estimates.

```
proc sort data=nhis3; by strat psu; run;
proc vargen data=nhis3 design=wr;
nest strat psu / missunit;
subpopn agegrp=1;
weight wtfa;
class srvy_yr;
xper perc : noins / value = 1 name = "Percent of adults who were uninsured";
parameter p : perc/100 / name="Proportion of adults who were uninsured";
parameter np: 1-p / name="Proportion of adults who were insured";
parameter g : log(p/(1-p)) / name="Logit of p: g(x)";
output nsum estim seestim varestim / filename=noins nsumFMT=F11.00 estimFMT=F11.10
seestimFMT=F11.10 varestimFMT=F11.10 replace;
run;
proc contents data=noins; run;
proc print data=noins; var srvy_yr variable _c1 nsum estim seestim varestim; where
_c1=1; run;
```

The annual survey estimates and transformed survey estimates produced by PROC VARGEN are displayed in Table XV. Untransformed percentage estimates are plotted in Figure XIV and transformed estimates (log-odds scale) are plotted in Figure XV.

Table XV. Original and transformed percentages with corresponding standard errors for U.S. adults ages 18–64 who were uninsured at the time of interview, by year

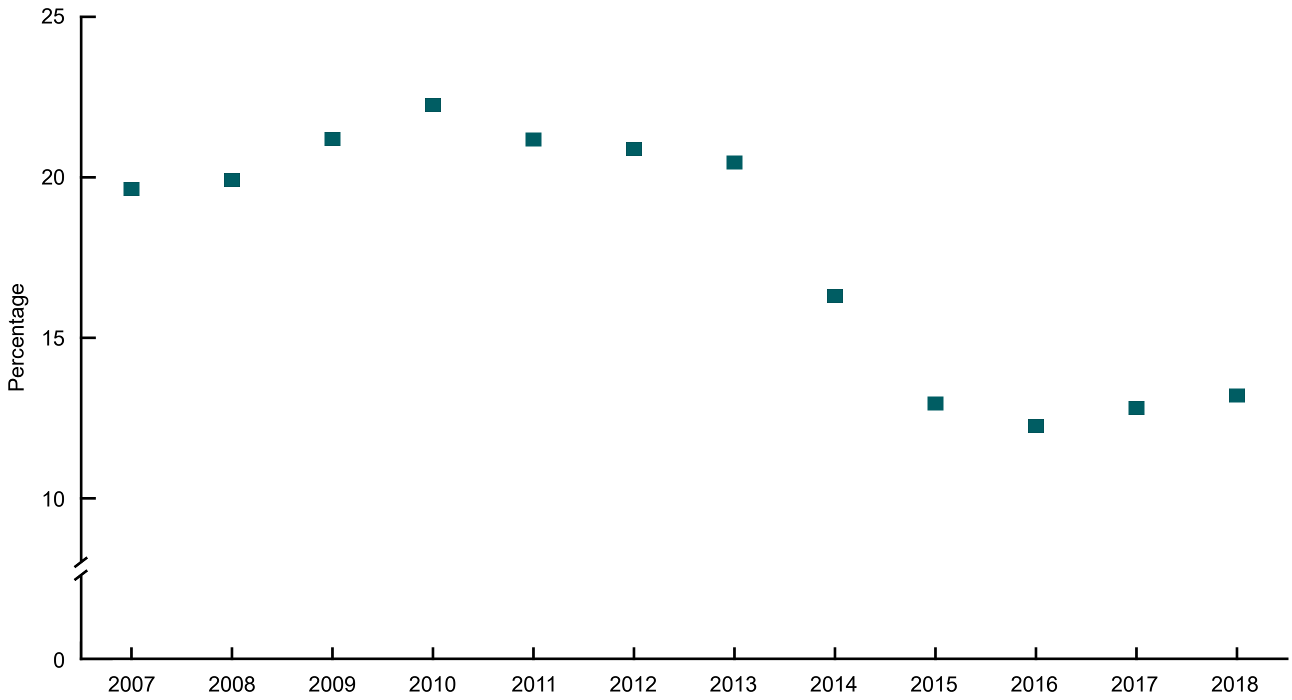
Year	*n*	Prevalence (weighted percent)	Standard error	Transformed prevalence estimate[1]	Transformed standard error[2]
2007	45,799	19.64	0.31	-1.41	0.02
2008	45,082	19.91	0.32	-1.39	0.02
2009	53,648	21.19	0.32	-1.31	0.02
2010	54,630	22.26	0.34	-1.25	0.02
2011	61,585	21.18	0.28	-1.31	0.02
2012	65,516	20.89	0.31	-1.33	0.02
2013	62,842	20.47	0.28	-1.36	0.02
2014	67,084	16.30	0.25	-1.64	0.02
2015	61,666	12.96	0.21	-1.90	0.02
2016	56,878	12.25	0.33	-1.97	0.03
2017	45,848	12.82	0.34	-1.92	0.03
2018	42,418	13.20	0.33	-1.88	0.03

[1]Percentages were rescaled to proportions (p = percent/100) and then transformed to the log odds scale by applying the formula $\ln(p/(1-p))$.
[2]Standard errors of the prevalence estimates were rescaled to be standard errors of proportions and then transformed to the log odds scale by applying the formula $se(p)/(p \bullet (1-p))$.

NOTES: An adult was defined as uninsured if they did not have any private health insurance, Medicare, Medicaid, state Children's Health Insurance Program (CHIP), state-sponsored or other government-sponsored health plan, or military plan. A person was also defined as uninsured if they had only Indian Health Service coverage or had only a private plan that paid for one type of service, such as accidents or dental care.

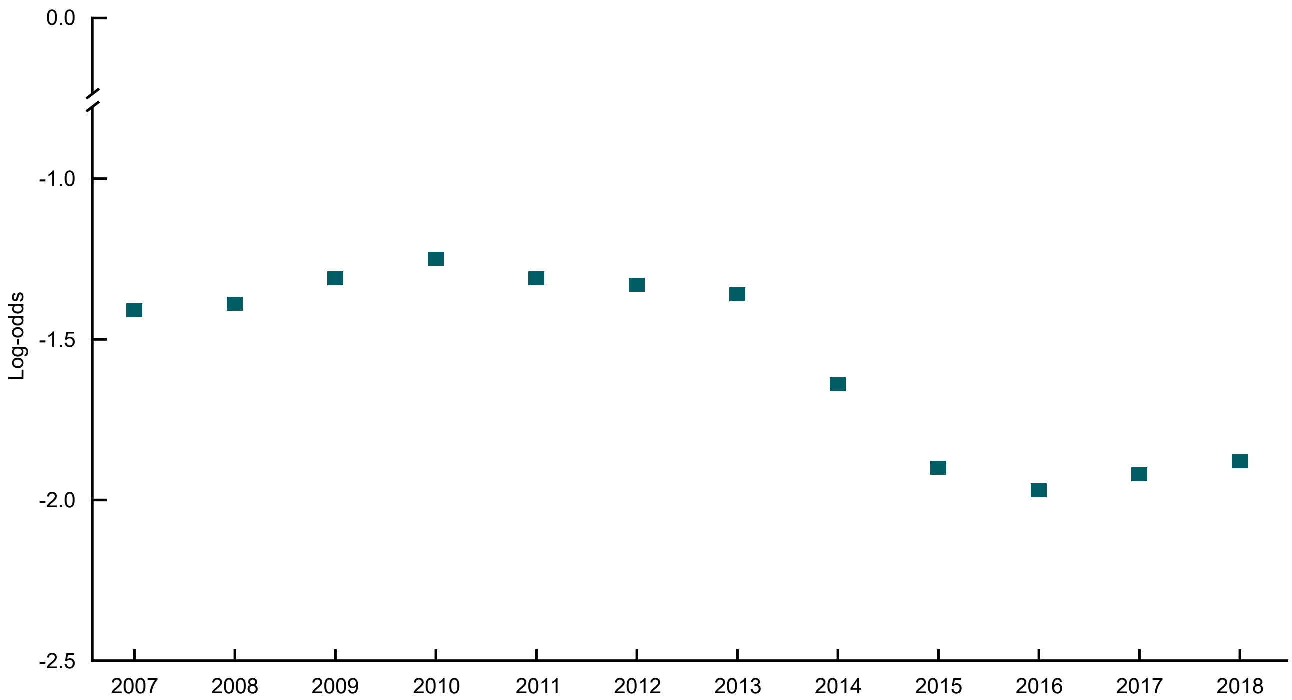
SOURCE: National Center for Health Statistics, National Health Interview Survey, Family Core component, 2007–2018.

Figure XIV. Percentage of U.S. adults ages 18–64 who were uninsured at the time of interview



NOTES: The analytic sample is adults ages 18–64. An adult was defined as uninsured if they did not have any private health insurance, Medicare, Medicaid, Children's Health Insurance Program (CHIP), state-sponsored or other government-sponsored health plan, or military plan. A person was also defined as uninsured if they had only Indian Health Service coverage or had only a private plan that paid for one type of service, such as accidents or dental care.
SOURCE: National Center for Health Statistics, National Health Interview Survey, Family Core component, 2007–2018.

Figure XV. Natural logarithm of the odds that a U.S. adult ages 18–64 was uninsured at the time of interview



NOTES: The analytic sample is adults ages 18–64. An adult was defined as uninsured if they did not have any private health insurance, Medicare, Medicaid, Children's Health Insurance Program (CHIP), state-sponsored or other government-sponsored health plan, or military plan. A person was also defined as uninsured if they had only Indian Health Service coverage or had only a private plan that paid for one type of service, such as accidents or dental care.
SOURCE: National Center for Health Statistics, National Health Interview Survey, Family Core component, 2007–2018.

Step 2: Obtain the Variance–covariance Matrix for Estimated Proportions Across Time Using PROC SURVEYMEANS in SAS/STAT Survey Procedures

SAS PROC SURVEYMEANS produces estimates and standard errors for proportions (p) but does not include the complement ($1 – p$).

```
proc surveymeans data=nhis3;
cluster psu;
strata strat;
weight wtfa;
var noins;
domain agegrp*srvy_yr / dfadj cov;
ods output
      Domain=noinsp
      DomainMeanCov=noinscov;
run;
proc print data=noinscov; where agegrp=1; run;
```

The variance–covariance matrix for estimated proportions across time, displayed through PROC PRINT, is provided in Table XVI.

Table XVI. Output from SAS/STAT representing the variance–covariance matrix for the proportion of adults ages 18–64 who were uninsured at the time of interview, by year

SRVY_YR[1]	Cov1	Cov2	Cov3	Cov4	Cov5	Cov6	Cov7	Cov8	Cov9	Cov10	Cov11	Cov12
2007	0.0000096	0.0000025	0.0000029	0.0000025	0.0000017	0.0000026	0.0000018	0.0000014	0.0000018	0.0000000	0.0000000	0.0000000
2008	0.0000025	0.0000100	0.0000033	0.0000020	0.0000018	0.0000012	0.0000015	0.0000011	0.0000013	0.0000000	0.0000000	0.0000000
2009	0.0000029	0.0000033	0.0000100	0.0000030	0.0000024	0.0000027	0.0000019	0.0000012	0.0000013	0.0000000	0.0000000	0.0000000
2010	0.0000025	0.0000020	0.0000030	0.0000120	0.0000031	0.0000023	0.0000025	0.0000018	0.0000016	0.0000000	0.0000000	0.0000000
2011	0.0000017	0.0000018	0.0000024	0.0000031	0.0000081	0.0000038	0.0000031	0.0000017	0.0000017	0.0000000	0.0000000	0.0000000
2012	0.0000026	0.0000012	0.0000027	0.0000023	0.0000038	0.0000095	0.0000034	0.0000028	0.0000016	0.0000000	0.0000000	0.0000000
2013	0.0000018	0.0000015	0.0000019	0.0000025	0.0000031	0.0000034	0.0000078	0.0000025	0.0000017	0.0000000	0.0000000	0.0000000
2014	0.0000014	0.0000011	0.0000012	0.0000018	0.0000017	0.0000028	0.0000025	0.0000065	0.0000014	0.0000000	0.0000000	0.0000000
2015	0.0000018	0.0000013	0.0000013	0.0000016	0.0000017	0.0000016	0.0000017	0.0000014	0.0000046	0.0000000	0.0000000	0.0000000
2016	0.0000000	0.0000000	0.0000000	0.0000000	0.0000000	0.0000000	0.0000000	0.0000000	0.0000000	0.0000110	0.0000068	0.0000054
2017	0.0000000	0.0000000	0.0000000	0.0000000	0.0000000	0.0000000	0.0000000	0.0000000	0.0000000	0.0000068	0.0000120	0.0000059
2018	0.0000000	0.0000000	0.0000000	0.0000000	0.0000000	0.0000000	0.0000000	0.0000000	0.0000000	0.0000054	0.0000059	0.0000110

[1]Represents survey year.

NOTES: SAS/STAT output comes from PROC SURVEYMEANS and PROC PRINT. An adult was defined as uninsured if they did not have any private health insurance, Medicare, Medicaid, Children's Health Insurance Program (CHIP), state-sponsored or other government-sponsored health plan, or military plan. A person was also defined as uninsured if they had only Indian Health Service coverage or had only a private plan that paid for one type of service, such as accidents or dental care. Cov1–Cov12 represent untransformed covariance estimates associated with estimated proportions across time.

SOURCE: National Center for Health Statistics, National Health Interview Survey, Family Core component, 2007–2018.

Step 3: Combine Estimated Proportions With Variance–covariance Data to Create a Final Data Set of the Untransformed Variance–covariance Matrix

Combine estimated proportions (*p*) from step 2 (data set: *estim*) with the variance–covariance data set from step 2 (data set: *cov*) to create a data set (*covp*) of the form shown below (Table XVII). A new variable (*np*) is defined to represent the complement of *p*. The variable '*srvy_yr*' serves as the id variable for merging and represents the year of the survey labeled 2007 through 2018.

```
data estim; set noinsp; if agegrp=1;
np=1-mean;
rename mean=p;
drop DomainLabel LowerCLMean StdErr UpperCLMean VarName agegrp;
run;
proc print data=estim; run;

data cov; set noinscov (keep=srvy_yr agegrp cov1-cov12); if agegrp=1;
drop agegrp;
run;
proc print data=cov; run;

proc sort data=estim; by srvy_yr; run;
proc sort data=cov; by srvy_yr; run;
data covp; merge estim cov; by srvy_yr; run;
proc print data=covp; run;
```

Step 4: Use SAS PROC IML and the Data Set Produced in Step 3 to Obtain the Transformed Variance–covariance Matrix

```
proc iml;
varNames = {"p" "np" "cov1" "cov2" "cov3" "cov4" "cov5" "cov6" "cov7" "cov8" "cov9"
"cov10" "cov11" "cov12"};
use covp;
read all var varNames into j2;
close covp;
print j2[c=varNames];

covl = j(12,12,1);
do i=1 to 12;
      do j=1 to 12;
      covl[i,j]=j2[i,j+2]/(j2[i,1]*j2[i,2]*j2[j,1]*j2[j,2]);
      end;
end;
print covl;
create covl from covl;
append from covl;
show contents;
close covl;
print covl;

data covlogit; set covl; run;
proc print data=covlogit; run;
```

The variance–covariance matrix for proportions, transformed to the log-odds scale and displayed via PROC PRINT, is presented in Table XVIII.

Table XVII. Output from SAS/STAT representing the combined data set

SRVY_YR[1]	*p*	*np*	Cov1	Cov2	Cov3	Cov4	Cov5	Cov6	Cov7	Cov8	Cov9	Cov10	Cov11	Cov12
2007	0.196370	0.80363	0.0000096	0.0000025	0.0000029	0.0000025	0.0000017	0.0000026	0.0000018	0.0000014	0.0000018	0.0000000	0.0000000	0.0000000
2008	0.199137	0.80086	0.0000025	0.0000100	0.0000033	0.0000020	0.0000018	0.0000012	0.0000015	0.0000011	0.0000013	0.0000000	0.0000000	0.0000000
2009	0.211925	0.78808	0.0000029	0.0000033	0.0000100	0.0000030	0.0000024	0.0000027	0.0000019	0.0000012	0.0000013	0.0000000	0.0000000	0.0000000
2010	0.222628	0.77737	0.0000025	0.0000020	0.0000030	0.0000120	0.0000031	0.0000023	0.0000025	0.0000018	0.0000016	0.0000000	0.0000000	0.0000000
2011	0.211819	0.78818	0.0000017	0.0000018	0.0000024	0.0000031	0.0000081	0.0000038	0.0000031	0.0000017	0.0000017	0.0000000	0.0000000	0.0000000
2012	0.208892	0.79111	0.0000026	0.0000012	0.0000027	0.0000023	0.0000038	0.0000095	0.0000034	0.0000028	0.0000016	0.0000000	0.0000000	0.0000000
2013	0.204743	0.79526	0.0000018	0.0000015	0.0000019	0.0000025	0.0000031	0.0000034	0.0000078	0.0000025	0.0000017	0.0000000	0.0000000	0.0000000
2014	0.163022	0.83698	0.0000014	0.0000011	0.0000012	0.0000018	0.0000017	0.0000028	0.0000025	0.0000065	0.0000014	0.0000000	0.0000000	0.0000000
2015	0.129551	0.87045	0.0000018	0.0000013	0.0000013	0.0000016	0.0000017	0.0000016	0.0000017	0.0000014	0.0000046	0.0000000	0.0000000	0.0000000
2016	0.122485	0.87751	0.0000000	0.0000000	0.0000000	0.0000000	0.0000000	0.0000000	0.0000000	0.0000000	0.0000000	0.0000110	0.0000068	0.0000054
2017	0.128160	0.87184	0.0000000	0.0000000	0.0000000	0.0000000	0.0000000	0.0000000	0.0000000	0.0000000	0.0000000	0.0000068	0.0000120	0.0000059
2018	0.132002	0.86800	0.0000000	0.0000000	0.0000000	0.0000000	0.0000000	0.0000000	0.0000000	0.0000000	0.0000000	0.0000054	0.0000059	0.0000110

[1]Represents survey year.

NOTES: SAS/STAT output comes from SAS PROC PRINT. The combined dataset (covp) includes the estimated proprortions of adults ages 18–64 who were uninsured at the time of interview (*p*), the complements of the proportions (*np*), and the variance–covariance data set (cov) for estimates by survey year (SRVY_YR). Cov1–Cov12 represent untransformed covariance estimates associated with estimated proportions by year.

SOURCE: National Center for Health Statistics, National Health Interview Survey, Family Core component, 2007–2018.

Table XVIII. Input data for Joinpoint regression software obtained using SAS PROC IML and representing the variance–covariance matrix for the proportion of adults ages 18–64 who were uninsured at the time of interview

COL1	COL2	COL3	COL4	COL5	COL6	COL7	COL8	COL9	COL10	COL11	COL12
0.0003857	0.0001008	0.0001104	0.0000911	0.0000650	0.0001012	0.0000692	0.0000666	0.0000983	0.0000000	0.0000000	0.0000000
0.0001008	0.0004064	0.0001249	0.0000718	0.0000675	0.0000439	0.0000564	0.0000527	0.0000726	0.0000000	0.0000000	0.0000000
0.0001104	0.0001249	0.0003711	0.0001053	0.0000870	0.0000979	0.0000710	0.0000514	0.0000706	0.0000000	0.0000000	0.0000000
0.0000911	0.0000718	0.0001053	0.0003936	0.0001063	0.0000811	0.0000893	0.0000751	0.0000805	0.0000000	0.0000000	0.0000000
0.0000650	0.0000675	0.0000870	0.0001063	0.0002891	0.0001382	0.0001148	0.0000744	0.0000920	0.0000000	0.0000000	0.0000000
0.0001012	0.0000439	0.0000979	0.0000811	0.0001382	0.0003487	0.0001246	0.0001252	0.0000880	0.0000000	0.0000000	0.0000000
0.0000692	0.0000564	0.0000710	0.0000893	0.0001148	0.0001246	0.0002924	0.0001121	0.0000923	0.0000000	0.0000000	0.0000000
0.0000666	0.0000527	0.0000514	0.0000751	0.0000744	0.0001252	0.0001121	0.0003465	0.0000907	0.0000000	0.0000000	0.0000000
0.0000983	0.0000726	0.0000706	0.0000805	0.0000920	0.0000880	0.0000923	0.0000907	0.0003608	0.0000000	0.0000000	0.0000000
0.0000000	0.0000000	0.0000000	0.0000000	0.0000000	0.0000000	0.0000000	0.0000000	0.0000000	0.0009193	0.0005648	0.0004371
0.0000000	0.0000000	0.0000000	0.0000000	0.0000000	0.0000000	0.0000000	0.0000000	0.0000000	0.0005648	0.0009345	0.0004620
0.0000000	0.0000000	0.0000000	0.0000000	0.0000000	0.0000000	0.0000000	0.0000000	0.0000000	0.0004371	0.0004620	0.0008543

NOTES: Each row in the table represents a survey year. The columns COL1–COL12 represent the covariance estimates associated with the log odds-transformed proportions for each of the 12 years from 2007 to 2018. The terms COL1–COL12 represent generic names produced from the SAS PROC IML code. Column names are not used in Joinpoint software when uploading the variance–covariance matrix.

SOURCE: National Center for Health Statistics, National Health Interview Survey, Family Core component, 2007–2018.

This variance-covariance matrix for proportions, transformed to the log-odds scale (Table XVIII), can then be input into the National Cancer Institute's Joinpoint Regression Software under the correlated errors option to continue evaluating the trend by assessing the number and location of joinpoints. Note that column headers must be removed before reading the variance-covariance matrix into the Joinpoint software.

In this example, both the untransformed and transformed variance-covariance matrices demonstrate independence between survey years with different sample designs (COL1–COL9 versus COL10–COL12). In these cases, no overlap in PSU and strata variables across time exists, and so the covariance terms associated with two estimates from different designs equal zero. Similar observations would be made for the entire matrix (off-diagonal elements) if using a data set such as the National Health and Nutrition Examination Survey, which assumes independence of PSUs and strata across time.

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