

National Center for Health Statistics Guidelines for Analysis of Trends

Data Evaluation and Methods Research



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

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Erratum notice: Revisions were made on pages 36–39 to reflect different design variables for calculating variance estimates using NHAMCS public-use data files. The previous version of this report utilized in-house design variables. The differences in results between the public-use and internal files were minimal and did not lead to changes in conclusions.

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

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Abstract

Background

Many reports present analyses of trends over time based on multiple years of data from National Center for Health Statistics (NCHS) surveys and the National Vital Statistics System (NVSS). Trend analyses of NCHS data involve analytic choices that can lead to different conclusions about the trends.

Objective

This report discusses issues that should be considered when conducting a time trend analysis using NCHS data and presents guidelines for making trend analysis choices.

Results

Trend analysis issues discussed include: choosing the observed time points to include in the analysis, considerations for survey data and vital records data (record level and aggregated), a general approach for conducting trend analyses, assorted other analytic issues, and joinpoint regression. This report provides 12 guidelines for trend analyses, examples of analyses using NCHS survey and vital records data, statistical details for some analysis issues, and SAS and SUDAAN code for specification of joinpoint regression models.

Conclusions

Several analytic choices must be made during the course of a trend analysis, and the choices made can affect the results. This report highlights the strengths and limitations of different choices and presents guidelines for making some of these choices. While this report focuses on time trend analyses, the issues discussed and guidelines presented are applicable to trend analyses involving other ordinal and interval variables.

Keywords: nonlinear trend • joinpoint regression • linear spline regression • health surveys • vital statistics

National Center for Health Statistics Guidelines for Analysis of Trends

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Introduction

National Center for Health Statistics (NCHS) staff produce many reports that present trends over time based on multiple years of data from NCHS surveys and data systems. For example, *Health, United States* presents an annual overview of national trends over time in health statistics (1). The Healthy People initiative regularly monitors progress over a decade toward targets that have been set for a large number of health objectives (2). The National Health Interview Survey (NHIS) Early Release Program regularly presents trends over time for health measures and health insurance coverage (3,4). *NCHS Data Briefs* and *National Health Statistics Reports* may also present trends over time using data from different NCHS data systems, such as NHIS (5); the National Health and Nutrition Examination Survey (NHANES) (6); the National Ambulatory Medical Care Survey (NAMCS) (7,8); the National Hospital Discharge Survey (NHDS) (9); the National Survey of Family Growth (NSFG) (10), and the National Vital Statistics System (NVSS)

(11). Trend analyses using NCHS data systems are also published regularly in scientific journals (12,13).

Most trend analyses conducted at NCHS involve time. Therefore, this report focuses on issues that should be considered when conducting a time trend analysis using NCHS data. For ease of exposition, the term “observed time points” is used to refer to the data points in a trend analysis. Issues discussed include: choosing the observed time points to include in the analysis ([Issues 1–4](#)); issues related to the type of data source ([Issues 5–6](#)); the general approach for conducting a trend analysis ([Issue 7](#)); other analysis issues ([Issues 8–10](#)); and joinpoint regression ([Issues 11–12](#)).

In addition to discussing these issues, this report presents guidelines for making trend analysis choices. The strengths and limitations of different choices are highlighted. Different choices can, and frequently do, lead to different conclusions about trends. There often is no single best way to conduct a trend analysis that is appropriate in all situations, and not all of the guidelines presented apply in all situations.

Following the sections on trend analysis issues and guidelines, this report provides illustrative examples of time trend analyses using data from NCHS data systems. [Appendices I–III, V, VI](#) provide statistical details for some trend analysis issues, and [Appendix IV](#) also provides SAS and SUDAAN code for specification of joinpoint regression models (14–16). To distinguish references to joinpoint regression methodology and the National Cancer Institute’s (NCI) Joinpoint Trend Analysis software, the report refers to the methodology as “joinpoint regression” and to the software using the capitalized terms, “NCI’s Joinpoint software” or “Joinpoint software” (17,18).

While this report focuses on trends over time, trends over other continuous or ordered variables such as age or income often are of interest. Many of the issues discussed in this report and the associated guidelines are generalizable and apply to trend analyses across variables other than time.

This report is not intended to be a comprehensive guide to trend analysis. Rather, it summarizes some issues that may arise when examining trends over time or over other types of ordered variable categories using NCHS data, and presents guidelines and possible justifications for making analytic choices.

Trend Analysis Issues and Guidelines

Trend analyses may be conducted using either record-level data or aggregated data. Record-level data refers to data for individuals, sample persons, or entities, while aggregated data refers to estimates previously computed from record-level data (e.g., rates, proportions, and percentages). The issues and guidelines presented below consider, when necessary, whether data are record-level or aggregated.

Choosing the Observed Time Points

Issue 1. Choosing the Time Period to Include in a Trend Analysis and Providing the Rationale

The time period to be included in a time trend analysis must be chosen and a rationale for the choice provided. The rationale is important because the time points included in the trend analysis impact the result of the analysis. The beginning and ending time points should not be chosen because of the result that they will give. For trend analyses that do not involve time, the whole range of values of the trend variable typically is used, so choice of beginning and ending points usually is not an issue. For time trend analyses involving NCHS data, generally only the beginning time point must be selected because the most recent time point available is typically the last point included in an analysis. When selecting a beginning time point, the following should be considered as possible rationales:

Data availability

Choice of the beginning time point depends, in part, on data availability. For example, the earliest time point that can be included in a trend analysis using the continuous NHANES is the 1999–2000 cycle, and the earliest time point that can be included in a national mortality analysis of Hispanic persons is 1997 (the year when all states began reporting Hispanic origin on the death certificate).

Data comparability

Data should be comparable across all time points included in the analysis. Reasons for lack of comparability include: changes in survey questions; changes in survey design; changes in the types of respondents for whom a data item is collected; changes in other data collection methods; changes in laboratory procedures; and changes in coding systems, such as the *International Classification of Diseases (ICD)*. For example, a major redesign of NHIS questionnaires occurred in 1997,

so including data prior to 1997 in a trend analysis of NHIS data may be problematic. Some trend models and software can accommodate lack of comparability, such as changes in the ICD version used to code cause of death (see “Jump Joinpoint Model” in [Issue 12](#)). In addition, if the analysis involves merging NCHS survey or vital records data with other data, comparability across time within the other data source may need to be considered.

External events

The timing of an external event may affect the choice of the beginning time point if an objective of the analysis is to assess the potential effect of an external event on the variable of interest. For example, did a new drug, medical device or procedure become available at a time that might affect the prevalence of the variable of interest? Was a new program implemented that could affect access to health care and impact the health measure of interest? Was there a shortage of a vaccine in a given year that could impact vaccination or disease rates? Note that often the timing of an external event does not coincide with the timing of a change in trend because the length of time before an external event has a measurable effect on the variable of interest varies.

Prior research

Has prior research involving the variable of interest identified a beginning time point for trend analyses?

Recent or long-term trend

Is there interest in recent trends such as the past 5 or 10 years or long-term trends such as the past two or three decades? For many health measures, the trends in the distant past may not be of as much interest as the trends in more recent years. Some analysts think it is better to include in the trend analysis the longest series of data available, even if there is interest only in the trend in recent years because inclusion of the longer-term data may help to establish the recent trend. However, inclusion of all available time points is not always appropriate for a number of reasons, and also may not be feasible. The choice of a

consistent, commonly used time period may be particularly useful in publications that examine multiple measures of health from multiple data systems. For example, the *Health, United States* Chartbook typically assesses changes in trend over a 10-year period.

Other rationales

The rationales for choosing a starting point listed above are not exhaustive. As an example, a starting point might be chosen so that the time period in the analysis matches that in another analysis. Alternatively, a significant year, such as the year 2000, might be chosen as the starting point.

Sensitivity of starting time point

If there is concern that the results of a trend analysis will differ depending on whether one or another adjacent time point is selected as the beginning of the time period, the analyst may wish to assess this by performing the analysis using alternative beginning time points. When appropriate, include this information in a discussion of the limitations of the analysis along with a rationale for the time period selected for the primary analysis.

Guideline 1

Provide a rationale for the choice of the time period included in the trend analysis. If there are concerns about the choice of the time period, discuss them, when appropriate, as a limitation of the analysis.

Examples of possible rationales for the choice of the time period include the following:

- a. The beginning time point is the first year that data for a variable of interest are available and the last time point provides the most recently available data.
- b. Data available prior to the beginning time point are not comparable to later data and the last time point provides the most recently available data.
- c. The time period was selected to include time points before and after the occurrence of an external event so that its impact on a health measure could be assessed.

- d. The beginning time point has been identified in previous research as the beginning of a trend of interest.
- e. The time period was selected to assess trends in the past 5 years (or 10 or 20 or another commonly used number of years), with some rationale for the choice.
- f. The year 2000 was chosen as the first time point because it is the beginning of the century and therefore a convenient and appealing starting point.
- g. The beginning time point was chosen to match the one used in another publication on the topic because it is of interest to compare results with the other publication.

Issue 2. Using all time points or just the beginning and ending time points to assess a trend

When data are available for three or more time points, the practice of measuring change over time by computing absolute change or the percent change between the beginning and ending time points and of testing the statistical significance of the change using a pairwise test ignores useful data. Such an approach assumes that there is a linear trend between the two time points or that any nonlinearities in the trend that occur during the time period are not of interest.

If a regression analysis of all time points shows no meaningful departures from a linear trend, then for ease of presentation, it may be desirable in some reports to calculate and report change between the beginning and ending time points. In some instances, the intent of the analysis may be to measure the difference between only two time points, as in the case of the Healthy People initiative which tracks change between a baseline time point and the most recent time point for a large number of health measures (2,19). The objective of these analyses is to measure progress toward target attainment for Healthy People objectives, rather than to assess trends across all time points. In another example, the annual report *Health, United States* presents an overview of national trends in health measures based on aggregated information that is shown

in a large number of tables and charts (1). *Health, United States* presents the results of trend analyses using all time points for a subset of the measures included in the report. However, data availability limitations and the large number of measures presented preclude detailed trend analyses based on all time points for all health measures.

Guideline 2

- a. In most situations, assess a trend and measure change using all time points rather than computing change using only the beginning and ending time points.
- b. If a trend analysis that uses all of the time points shows that the trend is linear, then for some types of reports, it may be desirable to report change between the beginning and ending time points.
- c. Measuring change between two time points may be necessary for reports that present large numbers of health measures, such as Healthy People and *Health, United States*.

Issue 3. Pooling data across years or cycles

Observed time points in trend analyses of NCHS data generally are single year or 2-year cycles because NCHS data typically are reported and analyzed as annual data, or for continuous NHANES and NSFG, starting in 2006 as 2-year cycles. It is possible to analyze NCHS data using some subannual levels (e.g., months and quarters) or subcycles (e.g., single-years for continuous NHANES and NSFG); however, subannual and subcycle survey data are not publically available and require use of different variance estimation methods. Analyzing subannual vital records data can be problematic because of issues such as seasonality.

Analyses of health outcomes in small subpopulations (e.g., preterm infants, HIV decedents, and Asians) or in geographic areas with small populations (e.g., states and sub-state areas), may produce point estimates with low precision or estimates that violate confidentiality restrictions. When this occurs, it is common practice

to pool multiple time points (years, cycles) to increase precision of the point estimates or comply with confidentiality restrictions, particularly if the data will be displayed graphically or in a table. When plotting a trend with unstable point estimates for the observed time points, pooling across time points produces a smoother plot of the trend, which may be desirable if a goal of the analysis is to display the data graphically. However, when conducting a trend analysis that involves fitting a model to the observed time points, pooling across the observed time points may not be desirable because it may increase the variance of the slope estimates obtained (see [Appendix II](#)) and could mask a change in trend or obscure when a change in trend occurred. An approach that can be used in such situations is to conduct the trend analysis using unpooled estimates but still display the pooled estimates. A disadvantage of this approach is that the unpooled analysis could identify a change in trend at a particular time point that is masked by the pooling, eliminating the connection between the description of the trend and the graphical appearance of the trend.

The caution about pooling across observed time points is intended to apply to pooling across single year or 2-year cycles (for continuous NHANES and NSFG), not to pooling across subannual or subcycle time points. As noted above, analyzing subannual or subcycle survey and vital records data can be problematic.

Guideline 3

- a. When assessing a trend by fitting a model, it generally is not desirable to pool data across the observed time points.
- b. Regardless of how a trend was estimated, if data for the time points used in the trend analysis cannot be displayed due to reliability or confidentiality guidelines or if the data values for the time points are unstable, pooled estimates could be displayed (provided the trend produced using pooled estimates does not differ substantively from that produced using unpooled estimates).

Issue 4. Choosing values to represent the observed time points

The values used to represent the observed time points in a trend analysis should reflect the spacing of those time points. Often data are available for each consecutive data year or cycle, in which case the observed time points are equally spaced. But sometimes data were not collected for the measure of interest for each consecutive data year or cycle (e.g., data on use of mammography among women were only collected in the 1987, 1993, 1994, 2000, 2003, 2005, 2008, 2010, and 2013 NHIS). Some NCHS surveys were not conducted at regular intervals. For example, prior to implementation of continuous NHANES which has consecutive 2-year cycles, starting with the 1999–2000 cycle, the survey was conducted during unevenly spaced multi-year periods (e.g., NHANES I, 1971–1975; NHANES II, 1975–1980; and NHANES III, 1988–1994). Trend analyses of obesity prevalence sometimes have included data from NHANES III and the 2-year cycles of continuous NHANES.

Values for equally spaced time points

When the observed time points in a trend analysis are equally spaced (e.g., a series of consecutive years or cycles), any set of values can be used to represent them provided that they are equally spaced. A common choice is to use the integers 0, 1, ..., T-1, or 1, 2, ..., T, where T is the number of observed time points. The values used will not affect the outcome of the test that the slope is zero, but can change the scale of the estimated slope and the location of the estimated intercept.

Example A. If an analysis includes annual estimates for 2000–2015, these annual values could be used in the trend analysis to represent the observed time points, or rescaled values could be used (e.g., 0 through 15 rather than 2000–2015).

Example B. If the observed time points in the trend analysis are equally spaced intervals, such as

consecutive cycles of continuous NHANES, the values used to represent them could be the beginning year of each 2-year cycle (e.g., 1999, 2001, ..., 2013), the midpoint of each cycle (e.g., 2000, 2002, ..., 2014), or a rescaled set of consecutive integers (e.g., 0, 1, ..., 9).

Values for unequally spaced time points

When the observed time points in a trend analysis are unequally spaced, the values used to represent them in a trend model should reflect the length of time between them. Additionally, if the observed time points are intervals of unequal length (e.g., NHANES III, which was conducted during 1988–1994), the time values chosen should take this into account.

Example C. If a trend analysis includes unequally spaced annual estimates (e.g., 1990, 1995, 1997, and 2000), the annual values could be used in the trend analysis to represent the observed time points because they reflect the length of time between the time points, or they could be replaced by other values that reflect the spacing (e.g., 0, 5, 7, and 10).

Example D. If the observed time points in a trend analysis are unequally spaced intervals of equal length (e.g., the continuous NHANES cycles of 1999–2000, 2001–2002, 2005–2006, and 2007–2008), the beginning year of each 2-year cycle (e.g., 1999, 2001, 2005, and 2007) or the interval midpoints (e.g., 2000, 2002, 2006, and 2008), or any set of values that represents the spacing of the cycles (e.g., 1, 2, 4, 5) could be used to represent the observed time points.

Example E. If the observed time points in a trend analysis are unequally spaced intervals and the intervals are of unequal length (e.g., 1988–1994, 1999–2000, 2001–2002, 2003–2004, 2005–2006), then the interval midpoints (e.g., 1991.5, 2000, 2002, 2004, 2006) could be

used to represent the observed time points or values representing the length of time between the midpoints could be used (e.g., 1, 9.5, 11.5, 13.5, 15.5).

Guideline 4

- a. When the observed time points in a trend analysis are equally spaced, any set of values can be used to represent them in a trend model, provided they are equally spaced.
- b. When the observed time points in a trend analysis are unequally spaced or are intervals of unequal length, the values used to represent them in a trend model should reflect this.

Conducting Trend Analyses

Issue 5. Considerations for trend analyses of survey data

Using record-level data

It is preferable to use record-level data rather than aggregated data when conducting trend analyses of survey data. Using record-level data allows the use of survey analysis software, such as SUDAAN, the R survey package, STATA, or SAS-survey, which properly takes into account all components of the survey design so that estimates are representative of the population, adjustment is made for year-to-year correlation, and the number of degrees of freedom used for hypothesis testing is properly computed. Software that uses only aggregated data, such as NCI's Joinpoint software, typically does not account for year-to-year correlation due to resampling primary sampling units (PSUs) because it cannot incorporate the full variance-covariance matrix and does not use the recommended degrees of freedom (based on the sample design). See [Issue 12](#) for a discussion of relevant features and limitations of NCI's Joinpoint software.

Estimation of the slope of a trend

The sample weights provided with survey data must be incorporated when estimating the slope of a trend line in order to produce an estimate that is representative of the population.

The “how and why” of incorporating sampling weights into a trend analysis can be found in a number of statistics books, including Section 3.5 of Korn and Graubard (20) and Chapter 7 of Heeringa, *et al.* (21). If sample weights are used properly, the estimate of the slope of a trend obtained using record-level survey data and that obtained using aggregated survey data tend to be fairly similar. (See [Appendix I](#) for an illustration of why this happens in three different ways that slopes have been estimated.)

Estimation of the variance of the slope

When record-level survey data are analyzed using survey analysis software, the survey design (including use of the full variance-covariance matrix) is incorporated into the computation of the variance of the slope of the trend. When survey data are analyzed using software that accepts only aggregated data (e.g., point estimates and their variances previously computed using record-level data and survey analysis software), additional design information, such as the full variance-covariance matrix or the recommended degrees of freedom typically cannot be incorporated. Despite this, in practice, estimates of the variance of a slope obtained using record-level data have been found to be, generally, fairly similar to those obtained using aggregated data, provided there is minimal year-to-year correlation, (see “Year-to-year correlation”). However, even if variance estimates from record-level and aggregated data analyses are similar, the results of hypothesis tests tend to be different (see “Hypothesis testing”).

Year-to-year correlation

Use of the full variance-covariance structure when estimating the variance of the slope of a trend is an important consideration when analyzing surveys for which some PSUs are in the sample for multiple years (e.g., NHIS). When PSUs appear in multiple years, year-to-year correlation may result because observations from the same PSUs are more likely to be positively correlated with each other than those from different PSUs. 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, for many stratified clustered population surveys, result in estimates of the variance of the slope that are too small. When record-level survey data are analyzed using survey analysis software, the variance-covariance structure of the data is fully incorporated and any year-to-year correlation adjusted for. When aggregated survey data are analyzed, the full variance-covariance structure of the data is not incorporated, so the year-to-year correlation cannot be correctly adjusted for (see [Issue 12](#) for a discussion of the features and limitations of NCI's Joinpoint software).

Hypothesis testing and degrees of freedom

An accurate test of trend is a function of an unbiased estimate of the slope, a precise estimate of the variance of the slope, and the recommended number of degrees of freedom. Trend analyses using record-level data and survey analysis software produce the most accurate tests of trends for survey data. As discussed above, analyses using aggregated survey data (previously generated by survey analysis software to incorporate sample weights and the survey design) tend to produce slope estimates similar to those obtained from analyses using record-level data, but with a corresponding estimated variance that tends to be somewhat smaller than it should be (depending on the amount of year-to-year correlation that is not accounted for). Thus, test statistics computed using estimates obtained from record-level and aggregated data often are similar, though those from aggregated data can, generally, be somewhat larger.

Despite similarities in the test statistics produced using record-level and aggregated survey data, tests of hypothesis can produce different results, largely because the number of degrees of freedom used by the two approaches may differ. For NCHS surveys, the recommended number of degrees of freedom for a hypothesis test generally is the number of PSUs minus the number of sampling strata. This is the number used when record-level survey data are analyzed using survey analysis software, but not the number used when

aggregated data are analyzed. The number of degrees of freedom used for hypothesis tests involving aggregated survey data typically is a function of the number of observed time points in the analysis and the number of parameters estimated. Thus, for NCHS surveys with a large number of PSUs (such as NHIS), the number of degrees of freedom for a record-level data analysis will be substantially larger than the number for an aggregated data analysis, unless the time trend is long. Therefore, tests of hypothesis from record-level data analyses are more likely to (correctly) detect departures from the null hypothesis than those from aggregated data analyses. For NCHS surveys with a relatively small number of PSUs, such as NHANES, the difference in the number of degrees of freedom for record-level versus aggregated data may be small and have little impact on test results. Additionally, the difference in the number of degrees of freedom may not be important if the number of degrees of freedom for the aggregated data analysis is large. Results of limited simulations indicate that when the number of observed time points in a trend analysis is 20 or more, the effect of the smaller number of degrees of freedom for an aggregated data analysis is minimal.

Exceptions to using record-level survey data

Assessing a nonlinear trend using joinpoint regression

When a trend analysis involves using NCI's Joinpoint software to fit a joinpoint regression model to a trend, aggregated survey data (point estimates and their standard errors previously computed using survey analysis software) must be used as the input data. Following the caveats mentioned earlier in this section, Joinpoint software (in its current version) does not correctly adjust for year-to-year correlation of the survey estimates or use the correct number of degrees of freedom for hypothesis tests. Because of these issues, it is recommended that NCI's Joinpoint software be used only to identify the joinpoints and that the slope and variance estimates and hypothesis tests produced by NCI's Joinpoint software not be used. Instead,

the following work-around is suggested for assessing the trend. Obtain the slope and variance estimates and hypothesis tests for the trend by fitting the joinpoint regression model that corresponds with the joinpoints identified by NCI's Joinpoint software to the record-level data using survey analysis software. See [Issue 12](#) for more information about the features and limitations of NCI's Joinpoint software and [Appendix IV](#) for information about how to parameterize a joinpoint regression model.

Large data reports

A concerted effort should be made to conduct record-level analyses of survey data. However, some reports present large numbers of tables compiled using aggregated data. Some tests of time trends in such reports may be done using aggregated data if record-level data are unavailable or if it is not feasible to conduct record-level data analysis for all time points. An example of such a report is the annual publication, *Health, United States* which provides an overview of trends in health statistics. When aggregated survey data are used to make statements about trends, a statement about the limitations of this approach must be provided.

Guideline 5

- a. When analyzing survey data, generally use record-level data and survey analysis software to fit the desired trend model so as to incorporate the survey design and sample weights, adjust for year-to-year correlation, and properly compute degrees of freedom.
- b. A partial exception to using record level survey data is made when changes in trend will be assessed using joinpoint regression models fit with NCI's Joinpoint software. NCI's Joinpoint software may be used with aggregated data to identify the number and location of joinpoints. Survey analysis software is then used with record-level data to obtain final slope estimates and tests of hypothesis for the model identified by the Joinpoint software ([Issue 12](#)).
- c. Aggregated survey data may be used for trend analyses in large data

reports when record-level analysis is either not possible or not feasible. However, the report should make note of this.

Issue 6. Considerations for trend analyses of vital records data

Using aggregated data

When time trend analyses of vital records data are conducted, aggregated data generally are used due to one or more of the following:

- The availability and accessibility of published rates, proportions, and percentages spanning multiple decades, in some cases;
- The relative ease of computing variances for the rates, proportions, and percentages;
- The need to employ specialized formulas, which are not always part of standard software programs, to compute the variances; and
- The need to use aggregated numerator and denominator values because the numerator and denominator data come from separate files that cannot be combined at the record level, and weights for the numerator must be incorporated (e.g., the period-linked birth and death files).

Year-to-year correlation

It is assumed when conducting time trend analyses of vital records data that there is minimal or no year-to-year correlation. Clearly, the year-to-year correlation due to resampling of PSUs that can affect survey data does not apply to vital records data. Vital events (deaths or births) occurring in one year are not inherently dependent on or correlated with vital events occurring in previous or subsequent years because a person can die or be born only once and one individual's birth or death (with rare exceptions) does not directly influence other such events.

Modeling vital records data

Typically, weighted least-squares regression models (with either a log-linear or linear function) are fit to

aggregated vital records data, with the weights being a function of the inverse of the estimated variance of the rates, proportions, or percentages. Trend analyses of the aggregated data can be performed using any software that can input rates or proportions and their estimated standard errors and perform a weighted least-squares regression. There are other modeling choices, particularly if record-level vital records data are being analyzed.

Log-linear models

Log-linear models (i.e., linear models of the natural logarithm of the outcome variable) are the most commonly used models for trend analyses of vital records data. These models are often used because they estimate the annual percent change (i.e., a constant percent change per year) and this metric provides an easily interpretable measure of change and also allows comparisons across groups that have very different observed data values (e.g., death rates for different age groups) or outcomes with very different data values (e.g., death rates for different causes). Note that when a log-linear model is used, the estimated annual percentage rate change is computed as $100 \cdot (\exp(\beta) - 1)$.

Linear models

Linear models estimate the absolute annual change (i.e., a constant absolute amount per year). For comparisons of groups with large differences in observed data values, this metric is less meaningful than the annual percent change (the metric estimated by the log-linear model). For example, death rates for elderly persons and children may change at the same annual percent per year, but because the rates for elderly persons are much higher than those for children, it is unlikely that they would change the same absolute amount per year.

Assessing a trend when there is a change in ICD coding

When conducting time trend analyses of mortality data, the analyst must take into account changes in the *International Classification of Diseases* (ICD) revision used to code cause of death because when there is a change in which ICD

revision is being used, a discontinuity in the cause-of-death trend results. Such discontinuities occur because of a change in scale, not because of a change in the underlying trend. Correction factors (referred to as comparability ratios) are estimated for different causes of death by “double-coding” (using both the old ICD codes and the new ICD codes) and are used to correct for the change in scale (22). The analyst must consider how suitable the available comparability ratios are for the cause of death being studied and for the subpopulation being studied. For trend analyses that include data from two or more ICD revision periods, the comparability ratio can be applied to the data for the years coded under the older ICD revision to transform them to the same scale as the later years, and then the trend model can be fit (note that the variance of the rate must be adjusted for the comparability adjustment). If NCI’s Joinpoint software will be used to fit the trend model, the software’s comparability ratio model (which accommodates the discontinuity by applying the appropriate user-supplied comparability ratio) or its jump model (which estimates the discontinuity from the data) can be used (Issue 12).

Assessing a change in trend using NCI’s Joinpoint software

When a trend analysis involves assessing whether or not there is a change in trend in vital records data, NCI’s Joinpoint software, which uses aggregated data (point estimates and their standard errors) as input, can be used to estimate the location of the joinpoints, fit the corresponding joinpoint regression model, and obtain slope estimates and tests of trend (Issues 11 and 12) (17, 18). All of the features of NCI’s Joinpoint software are appropriate for use with vital records data because: a) these data represent a complete census of births and deaths, not a sample, and thus, the issues that arise for survey data mostly do not apply, and b) it is assumed that there is minimal or no year-to-year correlation. Note that the joinpoint model fit by the Joinpoint software may differ depending on the software settings used and that there are no definitive rules for choosing

the settings. See Issue 12 for further discussion.

Guideline 6

- a. It is acceptable to use aggregated data for trend analyses of vital records data.
- b. NCI’s Joinpoint software can be used to fit a straight line or a joinpoint regression model (estimate the observed time points at which changes in trend occur, estimate the slopes of the line segments and their variance, and conduct hypothesis tests) to aggregated vital records data. Typically, the software’s weighted least-squares option is used.
- c. Log-linear models facilitate comparison of trends for groups or outcomes with large differences in observed data values. When a log-linear model is used, the estimated annual percentage rate change is computed as $100 \cdot (\exp(\beta) - 1)$.

Issue 7. General approach for conducting trend analyses

It generally is preferable to assess a trend by fitting a model to all of the observed time points in the time period of interest so that important features of the trend are not overlooked (Issue 2). The usual approach is to assess the trend for nonlinearity and then specify a model that is appropriate for both the data and the goals of the analysis. The steps followed to assess nonlinearity and to select and test the trend model depend on a number of factors including: whether the data are from a survey or vital records (Issues 5 and 6), whether the data are record level or aggregated (Issues 5 and 6), whether nonlinearity is detected, and the research question of interest. As the number of observed time points in a trend analysis increases, the complexity of the trend may increase and the analysis options also may increase.

When there are only three observed time points: trend analysis or pairwise comparisons?

When only three observed time points (or ordered categories of a variable) are available, changes in an outcome variable can be assessed using either a trend analysis or pairwise comparisons. If there is interest in determining whether the change in the outcome variable is nonlinear (quadratic) or linear, and if linear, whether it is increasing, decreasing, or stable, then a trend analysis should be performed. If instead of fitting a model to the trend, the analyst conducts pairwise comparisons, a justification should be provided. When using pairwise comparisons to quantify the differences between estimates for the observed time points (or ordered categories) and to determine which of the estimates differ from each other, all pairwise differences should be tested (three tests when there are three estimates). The significance level of the pairwise difference tests should be adjusted for multiple comparisons (e.g., using the Bonferroni method). Note that when using the pairwise comparison approach to assess differences among time points, the analyst should not pick only the last three time points for study without providing a justification for doing so ([Issue 1](#)). Further, if there is interest in determining if there is a change in trend at the last time point, it usually is preferable to make such an assessment within the context of a longer time series, not with only three time points (see “Assessing the last observed time point” in [Issue 12](#)).

Assessing nonlinearity in a trend

Four approaches for assessing nonlinearity in a trend are presented here: polynomial regression, orthogonal polynomial contrasts, joinpoint regression, and restricted cubic spline regression. When deciding which approach to use to assess nonlinearity, the analyst should consider the goal of the analysis, the type of data (survey data or vital records, record-level or aggregated), whether time points are equally spaced or not, whether covariates are involved, and whether a logistic model will be fit to the

trend. The assessment of nonlinearity will not always be consistent across these four methods (see below and [Issue 12](#)).

Polynomial regression

Nonlinearity can be assessed by fitting a polynomial regression model (i.e., a model with a linear time term and higher powers of the time variable) and comparing it with a lower-degree model to determine if the lower-degree model is adequate (23). Note that the higher the degree of a polynomial model, the better it will fit the data even if the incremental improvement in the fit is not statistically significant. Polynomial models of higher order than three are hard to interpret (23). Unless the linear and nonlinear time terms are parameterized to be orthogonal, they will be highly correlated. Such correlation among the time terms violates one of the basic assumptions of linear regression and higher-order polynomial models will be “ill-conditioned” and may have considerable errors in their estimated parameters. For lower-order polynomial models (quadratic, cubic), the correlation among the time terms is more of an inconvenience because it necessitates the use of backward or forward elimination procedures to fit the model. The time terms can be parameterized to be orthogonal (i.e., independent of each other), in which case the statistical significance of each term can be evaluated within a single model.

Typically, lower-order polynomial regression models are run with time terms that have not been parameterized to be orthogonal. If the linear and nonlinear time terms in the model are not orthogonal, then assessment of their statistical significance should be done using backward or forward elimination. For example, using backward elimination, if the initial polynomial model is cubic (in which case, the model includes a linear, a quadratic, and a cubic time term), the statistical significance of the cubic time term is tested. If the cubic term is statistically significant, it is concluded that a nonlinear trend is indicated (note that the statistical significance of the linear and quadratic terms in the cubic model is not informative). If the cubic term is not statistically significant, it is

dropped, the reduced model (with the linear and quadratic time terms) is fit, and the significance of the quadratic term is tested. If the quadratic term is statistically significant then a nonlinear trend is indicated; if not, then a model with just the linear term is fit and the significance of the linear term is tested to determine if the trend is increasing, decreasing, or stable. In general, polynomial regression is appropriate for most trend analyses and can accommodate unequally spaced time points, covariates, and logistic regression modeling. This approach may be used with record-level or aggregated data, depending on the type and source of the data ([Issues 5](#) and [6](#)). Using polynomial time terms to assess whether or not a trend is nonlinear has the advantage of simplicity. However, a disadvantage is that the polynomial models can only model certain forms of nonlinearity and may not adequately describe some trends.

Orthogonal polynomial contrasts

Orthogonal polynomial contrasts were developed in the context of the analysis of variance to assess trends (linear, quadratic, etc.) in the means of a response variable when the treatment (factor) levels are categorical. Orthogonal contrasts completely partition the treatment sum of squares into non-overlapping additive components that represent the variation due to each contrast. When a trend analysis is conducted using record-level data, orthogonal polynomial contrasts generally can be used to assess nonlinearity in the outcome variable across the observed time points. For example, if the data are record-level survey data, the POLY function in SUDAAN’s PROC DESCRIP uses polynomial orthogonal contrasts to assess nonlinearity up to the specified degree (16). The analyst determines the highest-order orthogonal polynomial contrast to test; as for polynomial regression, generally the higher-order terms should be limited to quadratic or cubic. As for polynomial regression, assessment of nonlinearity begins with the highest-order contrast. For example, if the highest-order orthogonal contrast is cubic (in which case linear, quadratic, and cubic contrasts will have been

produced), the statistical significance of the cubic contrast is evaluated first. If the cubic contrast is statistically significant, a nonlinear trend is indicated (note that in this case the statistical significance of the linear and quadratic contrasts is not informative). If the cubic contrast is not statistically significant, the quadratic contrast is evaluated for significance. If the quadratic contrast is statistically significant, then a nonlinear trend is indicated; if not, the linear contrast is evaluated for significance. If only the linear orthogonal polynomial contrast is significant, then the trend is linear.

An advantage of the polynomial contrast approach is that the linear and higher-order contrasts are obtained from a single request, rather than from sequential requests. A disadvantage of the orthogonal polynomial contrast approach is that it cannot accommodate covariates; if covariates will be included in the trend model, a polynomial regression model rather than orthogonal polynomial contrasts should be used to assess nonlinearity so that the estimates can be adjusted for the covariates. Also, orthogonal polynomial contrast assessments conducted in SUDAAN and SAS are on the linear scale, so if the underlying model of interest is logistic, this approach is not appropriate and instead a polynomial regression model should be used to assess nonlinearity. While the results of an assessment of nonlinearity carried out on the linear scale may be the same as those obtained from an assessment carried out on a logistic scale, this will not always be the case, as an assessment for linearity can produce different results for data that are on the linear scale than for the same data on the logistic scale.

When the sample is large and the population is stable over time, the orthogonal polynomial contrast approach can produce results approximately equal to those produced by a polynomial regression model if the observed time points are equally spaced, the polynomial terms in the regression model are orthogonal, a linear regression model is being fit, and there are no covariates in the model (see [Appendix III](#) which illustrates the special case of three time points).

SUDAAN and other software routinely generate the coefficients for the orthogonal polynomial contrasts when the observed time points are equally spaced; orthogonal polynomial contrast coefficients for unequally spaced time points require special handling (24).

Joinpoint regression

Another method for assessing nonlinearity is to fit a joinpoint regression (linear spline or piecewise linear regression) model to the trend. Joinpoint regression models consist of two or more linear segments connected at specified time points (called joinpoints) at which a change in trend occurs (see [Issues 11 and 12](#), [Appendix IV](#), and pages 346–348 of Chapter 10: Indicator Variables in Neter, Wasserman, and Kutner) (25). To fit a joinpoint regression model, both the number and location of the joinpoints must be estimated. If a trend has one or more joinpoints, it is considered to be nonlinear. This approach offers more flexibility for modeling nonlinearity than polynomial regression does, as it facilitates modeling curves that do not have the standard polynomial shapes (e.g., quadratic or cubic) and can better accommodate abrupt changes in trend. NCI's Joinpoint software can be used to fit joinpoint regression models and estimate the number and location of joinpoints. This software requires aggregated data (which as discussed in [Issue 5](#) is problematic for survey data) and cannot directly accommodate covariates ([Issues 9 and 12](#)). The number and location of joinpoints identified may differ with the software settings used (see [Issue 12](#) for further discussion).

Restricted cubic spline regression

Nonlinearity also can be assessed by fitting a cubic spline regression model to the trend. See “Regression Splines,” page 97–100 and [Appendix C](#) in Korn and Graubard (20) and Durrleman and Simon (26). A cubic spline model consists of a series of polynomial curves (with the highest-order term for any curve being cubic) that are connected at specified time points. A restricted cubic spline model is a cubic spline model with the first and last curves restrained to be linear. The number and location of the

joinpoints typically are specified by the analyst. The number of joinpoints must be small enough to ensure that there are sufficient observed time points in each interval to estimate a cubic polynomial curve. Their locations often are specified so that the time period is divided into intervals of equal length or into desired quantiles. Cubic spline models provide a detailed portrayal of the behavior of the outcome variable over the time period. Cubic spline models can be fit to record-level or aggregated data. Currently, to implement a cubic spline model, the analyst can write SAS code to create spline variables which are then input into an appropriate regression procedure (e.g., for record-level survey data they could be input into SUDAAN's PROC REGRESS or PROC RLOGIST). User-supplied spline procedures are available in STATA and R, though they may not be appropriate for complex survey data.

Modeling a trend

If a nonlinear trend is not indicated, a regression model with a linear time term can be fit to the observed time points to estimate the direction and magnitude of the slope. For survey data, the linear trend should be fit using record-level data and survey analysis software when possible ([Issue 5](#)). For vital records data, if the trend will be fit to aggregated data, slope estimates and hypothesis tests for the linear trend can be obtained from NCI's Joinpoint software or from any software that can input rates or proportions and their estimated standard errors and perform a weighted least-squares regression ([Issue 6](#)).

If a nonlinear trend is indicated or is of interest for *a priori* reasons, various models can be fit to the data. Acceptable ways to model a nonlinear trend include fitting a regression model of some sort with polynomial time terms, a joinpoint regression model, or a cubic spline model. Joinpoint regression models are described in detail in [Issues 11 and 12](#); and in [Appendix IV](#).

The nonlinearity assessments obtained from joinpoint and cubic spline regression models may not be easily compared to those obtained from other types of models. For example,

the degree of nonlinearity identified by a polynomial regression model may appear to be inconsistent with the number of joinpoints identified by joinpoint regression or restricted cubic spline regression models. This inconsistency reflects both differences in the forms of nonlinearity the various approaches can detect and at times the greater flexibility of the joinpoint and cubic spline regression approaches to model the diverse forms that trends can take.

Guideline 7

- a. When there are only three observed time points, a test for trend can be performed to determine whether the trend is nonlinear or linear (and if linear, whether it is increasing, decreasing, or stable). A justification should be provided if instead of fitting a trend model, the pairwise differences among the three observed time points are quantified and tested (the tests' significance levels should be adjusted for multiple comparisons).
- b. To assess a trend for nonlinearity, consider using polynomial regression, orthogonal polynomial contrasts, joinpoint regression, or restricted cubic spline regression (if there are sufficient observed time points).
- c. If a trend is nonlinear and a goal of the analysis is to model the nonlinearity to improve the fit of the model, consider fitting a regression model with polynomial time terms. If a trend is nonlinear and a goal of the analysis is to identify where changes in trend occur and to quantify them, consider fitting a joinpoint regression model.

Other Analytic Issues and Guidelines

Issue 8. Trend analyses with binary outcome variables

A trend analysis with a binary outcome variable estimates the trend in the probability of the outcome occurring. A number of regression approaches can be used to fit a trend to a function of a

probability, including logistic regression, complementary log-log regression (i.e., $\log\{-\log(1-p)\}$), probit regression, and linear probability regression (27,28). Some of these approaches ensure that the predicted probability will only take values between 0 and 1 and some do not. Probabilities must always be between 0 and 1 and as a consequence, a predicted trend line that contains values outside the 0–1 range is unacceptable because this logically cannot occur. Most trend analyses of NCHS data that involve a binary outcome variable fit either a logistic or a linear model to the trend.

Using a logistic model

Logistic regression is a commonly used modeling approach when the outcome variable is binary. The logistic model assumes that the natural log of the odds, $\ln(p/(1-p))$, is a linear function of the independent variables (e.g., time and any covariates). An advantage of the logistic model is that the predicted trend line will always be in the unit interval, but the disadvantage is that interpreting the log odds or the odds ratio is not intuitive, and so the information about the trend that can be obtained from the slope estimates is not as useful as that obtained from a linear or log-linear model. To illustrate this, if the regression coefficient for the time variable in a logistic model is 0.05, that means that a 1-unit increase in time (e.g., 1 year or 1 cycle) is associated with a 0.05 increase in the log odds that the outcome variable has the value 1. This measure does not provide easily interpretable information about the magnitude of the change in trend. Estimates of the slope of a trend line obtained from a logistic model must be interpreted in terms of the log-odds of the probability of the binary outcome and should not be used as a proxy to explain a trend based on another scale, such as a log or linear scale.

When logistic regression is used for the trend analysis, there are several analytic considerations. One of these is that it may not be appropriate to use orthogonal polynomial contrasts to assess nonlinearity because the orthogonal terms are on the linear scale; they are not on the logistic scale (see [Issue 7](#),

Orthogonal Polynomial Contrasts). Another consideration is that if NCI's Joinpoint software will be used to identify joinpoints and a logistic model will be used to obtain final estimates of the trend, the proportions and their standard errors should be transformed to the log-odds scale before inputting them into the Joinpoint software ([Issue 12](#) and [Appendix VI](#)). Also see the description of the transformation on page 32 of Cox's *The Analysis of Binary Data* (29).

Using a linear model

Analysts may prefer to fit a linear model to a trend with a binary outcome variable because the linear model yields slope estimates that are easy to interpret. However, it is not always appropriate to use linear regression to fit a trend to a binary outcome because this model does not ensure that the predicted probabilities will be in the unit interval. For a more detailed discussion, see "A binary dependent variable: the linear probability model," pages 238–243 of Wooldridge's *Introductory Econometrics: A Modern Approach* (30). For trend analyses of NCHS data, it is recommended that a linear model be fit only when all of the predicted probabilities lie in the unit interval. A more conservative approach would be to also require that the 95% confidence intervals around the predicted probabilities all lie within the unit interval. If the predicted probabilities are in the mid-range of the unit interval (e.g., between 0.2 and 0.8), then the logistic and linear models produce similar results (except that the logistic results are harder to interpret) (31). Because being able to make statements about the magnitude of a change in trend (in addition to the direction of the change) is often of interest, it may be preferable to fit a linear regression model, rather than a logistic model, to a binary outcome variable when conducting a trend analysis. When fitting a linear trend to binary data, the outcome variable should be coded as either 0 or 1 (to estimate probabilities) or as 0 or 100 (to estimate percentages).

Guideline 8

- a. When the outcome variable is binary, a logistic model often is fit to the trend. If NCI's Joinpoint software will be used to identify joinpoints and a logistic model will be used to obtain final estimates of the trend, transform the proportions and their standard errors to the log-odds scale before inputting them into Joinpoint.
- b. Using a linear model rather than a logistic model when conducting a trend analysis on a binary outcome variable may be preferable because it provides more interpretable slope estimates. A linear model can be fit to binary data (coded as "0" and "1" or as "0" and "100") if the estimated trend line is within the unit interval for the time points under study.

Issue 9. Trend analyses with covariates

A trend analysis that involves covariates generally is conducted using record-level data. When the analyst wishes to include covariates in a trend analysis, the analytic approach outlined in [Issue 7](#) is followed, with a few modifications.

Assessing nonlinearity

When covariates are involved, nonlinearity can be assessed using a polynomial regression model, a modification of the joinpoint regression approach, or a restricted cubic spline model. Generally, orthogonal polynomial contrasts should not be used because they are not adjusted for the covariates. The joinpoint regression approach, if implemented using NCI's Joinpoint software, must be modified because covariates cannot be directly input into NCI's Joinpoint software. (See "Modeling a nonlinear trend using NCI's Joinpoint Software" below.)

Modeling a trend

If the trend is linear, then standard modeling approaches can be used to fit a regression model with covariates. If the trend is nonlinear, standard methods that combine polynomial time terms with covariates or fit a joinpoint regression

model with covariates can be used to fit a regression model to the trend.

Modeling a nonlinear trend using NCI's Joinpoint software

When a trend analysis involves both nonlinearity and covariates and the analyst wishes to fit a joinpoint regression model to the trend, it is desirable to take the covariates into account when selecting the joinpoint model, so that the estimates for each time point reflect adjustment for the covariates and their interactions. Using adjusted estimates usually affects the trend model that is fit (including the intercept of the model, the location of any joinpoints, and the slopes of the line segments) because the trend may vary for different combinations of covariate values. If NCI's Joinpoint software will be used to estimate joinpoints in the trend, the approach used for the trend analysis will differ somewhat from that used when there are no covariates because the covariates cannot be input directly into the software. If the covariates can be represented by a small number of subgroups and the sample sizes are sufficient, one approach is to treat the covariates as "by" variables and use the Joinpoint software's provisions for testing that two trends are coincident (identical) or parallel. Using this approach is equivalent to performing a stratified analysis with a separate model fit to each subgroup. The usual modeling strategies and considerations for a stratified analysis apply. Except when the trends for the different subgroups are found to be coincident, this approach does not produce an estimate of the "overall" trend for the total population of interest (adjusted for the covariates), which is often the goal of the analysis. However, as for any stratified regression analysis, if the trends across subgroups differ substantially (particularly when there are significant interactions between subgroups and time), conducting a trend analysis for the combined subgroups may be inappropriate. An alternative approach is to compute predictive margins (also referred to as predicted margins) and their standard errors and input these into the Joinpoint software. Using predictive

margins is a standard approach for directly adjusting for covariates and their interactions. This approach produces an "overall" estimate of the trend for the total population of interest. As noted above, if the trends for some subgroups differ substantially from each other, estimating the overall trend may not be appropriate. The predicted margins can be obtained from both linear and logistic regression procedures (using survey analysis software or other regression software) (32). Note that if logistic regression is used to model the trend and NCI's Joinpoint software will be used to locate joinpoints, it is recommended that the predictive margins and their standard errors be transformed to the log-odds scale before being input into the Joinpoint software. An issue with using predictive margins as input to NCI's Joinpoint software is that they will be correlated across the time points (because they were all generated using the same regression model). This year-to-year correlation will have some effect on the permutation test and the Bayesian Information Criteria used by NCI's Joinpoint software to estimate the number and location of joinpoints ([Issues 5, 7, and 12](#)).

The approach used to obtain the final slope estimates and hypothesis tests for a trend analysis that involves covariates is essentially the same as that used when there are no covariates. For a trend analysis using record-level survey data, the final slope estimates and hypothesis tests are obtained using survey analysis software to fit the joinpoint regression model corresponding to the joinpoints estimated by NCI's Joinpoint software and including the covariates ([Issues 5, 7, and 12](#)). For vital records data, the final slope estimates and tests could be obtained from the Joinpoint program per usual. However, when possible, it is preferable to fit the model corresponding to the estimated joinpoints using software that can directly incorporate the covariates.

Guideline 9

- a. If the trend is linear, covariates can be included in trend analyses using standard modeling approaches.

- b. If the trend is nonlinear and will possibly include joinpoints, it is preferable to incorporate the covariates in the analysis when estimating the number and location of any joinpoints.

Issue 10. Cochran-Mantel-Haenszel test for trend

The Cochran–Mantel–Haenszel test for trend (CMHT) and the ANOVA-type CMH test (ACMH) can be used to test for linear trend in an $R \times C$ table or a set of stratified $R \times C$ tables, where the rows (R) represent the categories of the dependent variable and the columns (C) represent the categories of the independent variable. For a trend analysis, the row variable often is a binary outcome variable and the column variable is time. The CMHT tests for a linear association between the row and column variables of an $R \times C$ table or a stratified set of $R \times C$ tables, when both variables are ordinal (33–35). The ACMH tests whether for any stratum, there are differences among the rows in the mean column scores (33,34). For the ACMH, the row variable is nominal and the column variable is ordinal.

The CMHT and ACMH tests do not provide an assessment of nonlinearity. Nor do they provide an estimate of the slope of the trend or indicate the direction of the trend. Thus, for many trend analyses, these two tests will not be useful. However, these tests may be useful when there are multiple $R \times C$ tables or the dependent variable has more than two categories.

When the row (dependent) variable is binary, the CMHT and ACMH tests are equivalent. Additionally, when the row variable is binary and the column (independent) variable is interval, the result of a CMHT test using SUDAAN generally will be similar to the assessment of linear trend obtained by fitting a linear regression model. An illustrative example of this similarity using the CMH description from the *SUDAAN 11 Language Manual* is provided in [Appendix V](#) (16).

The CMHT and ACMH tests can be applied to record-level survey data using survey analysis software such as

SUDAAN (PROC CROSSTAB) and to record-level vital records data using standard software such as SAS (PROC FREQ) (14–16).

Guideline 10

When outcomes are ordinal or nominal with three or more categories the CMH test for trend may be useful. When an outcome is binary, a CMH test of linear time trend using SUDAAN will be similar to the results from a linear regression model.

Joinpoint Regression

Joinpoint regression (also referred to as piecewise regression, change-point regression, segmented regression, and linear spline regression) characterizes trends by fitting a model consisting of two or more linear segments that have different slopes and are connected at the time point or points where a change in trend occurs (referred to as joinpoints, change points, or knots). See “Piecewise Regression” in Chapter 10: Indicator Variables of Neter, Wasserman, and Kutner (25). See [Appendix IV](#) for details about model parameterization. Joinpoint regression provides an easily interpretable characterization of nonlinear trends, and thus is useful for describing and evaluating changes over time in health measures.

As with any statistical modeling approach, the estimated joinpoint model will depend on the data and on the model specifications and the computational algorithms used. For example, if the modeling procedure identifies the set of joinpoints that provide the best fit over the entire time period, then changing the time period included in the trend analysis (either the beginning or ending time points) may impact the estimated number and location of joinpoints. Similarly, running a time trend analysis with updated data for the ending time point (reflecting a different data value or a change in the accuracy of the estimate) may impact the estimated trend. Using different computational algorithms to estimate the number and location of joinpoints may yield different solutions. The characteristics of the trend also

affect the joinpoint model that is fit. Marked changes in trend are likely to be consistently identified, whereas small changes in trend or changes in trend at the end of a time period (when power to detect is low) may be identified by some procedures and not by others. See [Issue 12](#) for a discussion of the impacts of different settings for NCI’s Joinpoint software on the resulting joinpoint models.

Issue 11. Locating joinpoints at or between observed time points

The joinpoints of a joinpoint regression model are the points at which a change in trend occurs and also the points at which two adjacent line segments of the model connect.

Typically, the joinpoints are constrained to occur at observed time points (those for which there are data), but some modeling approaches allow them to be located between such points. Allowing the joinpoints to be located between observed time points can result in a better fit of the line segments to the trend data and thus better estimates of the trend slopes, particularly when there are sharp changes in the trend (e.g., changes in prostate cancer incidence that occurred after PSA screening was initiated). In general, however, there are several disadvantages to allowing joinpoints to be located between observed time points when analyzing NCHS data:

- NCHS data generally are reported and analyzed as annual data (or for continuous NHANES and NSFG, as 2-year cycles). Allowing a joinpoint to fall between observed time points makes interpretation of the changes in the trend conceptually problematic. It would be incorrect to interpret a joinpoint located between two observed time points as the actual time when the trend changed. This is particularly true for vital records data because there can be considerable seasonal variation in birth and death rates, and a trend fit to the annual data does not reflect this seasonal variability. When a joinpoint falls between two observed time points, not only is it incorrect to

interpret the location of that joinpoint as the time when a change in trend occurred, it also can be awkward to describe when a change occurred.

- When using NCI's Joinpoint software to estimate joinpoints, if a joinpoint falls between two observed time points, some line segments have slopes and standard errors that cannot be estimated due to too few observed time points between joinpoints ([Issue 12](#)).

If the analyst wants to look for joinpoints between the usual observed time points when analyzing survey data (e.g., between years for NHIS or between 2-year cycles for continuous NHANES or NSFG), it generally is preferable to use observed data for the subannual level of interest (e.g., months, quarters) or subcycle (e.g., single years) when available rather than allow joinpoints to fall between observed time points. However, if survey data are not available at the desired subannual or subcycle level, allowing joinpoints to fall between observed time points may sometimes be warranted (e.g., when there is an abrupt change in trend). When analyzing trends in vital records data, it generally is preferable to use annual data rather than subannual data because of variations in birth and death rates due to seasonality, although allowing joinpoints to fall between years also may sometimes be warranted.

Guideline 11

- Generally specify that joinpoints be located at observed time points, not between them.
- If joinpoints are located between observed time points, interpreting a joinpoint as the actual time when a trend changes is an incorrect interpretation.

Issue 12. Trend analyses using joinpoint regression and NCI's Joinpoint Trend Analysis software

This section focuses on the use of joinpoint regression to characterize a nonlinear trend and on the use of NCI's Joinpoint Trend Analysis (Joinpoint

software to fit joinpoint models (17,18). At NCHS, joinpoint regression is often used because a common analytic goal is to produce a description of the trend that includes identifying when changes in the trend occurred as well as the nature and significance of any changes. NCI's Joinpoint software fits joinpoint regression models to aggregated trend data (17,18,36,37), and has been useful for joinpoint regression analyses because its algorithms estimate both the number and location of joinpoints. Generally, the location of a change in trend is not known, although sometimes an approximate location is hypothesized ([Issue 1](#)). It is sometimes possible to identify a joinpoint through visual examination of the trend data, but more often the timing of a change is not obvious because the change is subtle or there is volatility among the observed estimates. The Joinpoint software sorts through the many possible joinpoint models and selects the one that best fits the data according to the algorithms used. However, the software was developed for trend analyses of aggregated administrative record data such as cancer incidence data and mortality data, rather than survey data. Because the Joinpoint program was not designed for use with surveys, it currently is recommended that for analysis of survey data, NCI's Joinpoint software be used to estimate the number and location of joinpoints, but not to estimate and test the slopes of the line segments corresponding with those joinpoints. In addition, as with any statistical modeling approach, the model selected will depend on the software settings used (particularly which model-fitting algorithm is used), and for some trends, different settings will yield different joinpoints.

Issues with modeling a trend with NCI's Joinpoint software

Inconsistencies in assessment of nonlinearity obtained from orthogonal polynomial contrasts, polynomial regression, and joinpoint regression

Joinpoint regression models may not be easily compared to polynomial regression models or orthogonal polynomial contrasts. While polynomial regression and orthogonal polynomial

contrasts generally produce nonlinearity assessments similar to each other, the degree of nonlinearity identified by these two approaches may sometimes appear to be inconsistent with the number of joinpoints identified by joinpoint regression models. This inconsistency reflects both differences in the forms of nonlinearity the various approaches can detect and at times, the greater flexibility of the joinpoint regression approach to model the diverse forms that trends can take. When the intent is to use a joinpoint regression model to characterize a trend that polynomial regression or orthogonal polynomial contrasts have identified as nonlinear, the degree of the significant polynomial term may be considered when setting the number of joinpoints to search for in the joinpoint model, but should not be considered to definitively indicate the number of joinpoints expected. For example, if polynomial regression or orthogonal polynomial contrasts find a significant quadratic term, consider searching for at least one joinpoint, but possibly more (particularly if a larger number would be allowed under the Joinpoint software defaults). The number of joinpoints identified by NCI's Joinpoint software can differ depending on the software settings used, and there are no definitive rules for choosing the settings (see below for further discussion).

Joinpoint regression analyses for record-level survey data

Because not all of the estimation and hypothesis testing procedures provided by NCI's Joinpoint software are appropriate for complex survey data ([Issue 5](#)), when conducting a joinpoint regression analysis using record-level survey data, it is currently recommended that NCI's Joinpoint software be used only to estimate the number and location of the joinpoints. It is further recommended that the joinpoint model (specified by NCI's Joinpoint software) be fit using record-level data and survey analysis software to obtain slope estimates and tests of hypotheses ([Issue 5](#)). For trend analyses that involve age-adjusted rates, a logistic model, or covariates, there are some additional considerations:

- If a trend analysis involves inputting age-adjusted rates (computed using counts for a standard population, such as those in the year 2000 U.S. standard population) to NCI's Joinpoint software, fitting the final joinpoint model in the survey analysis software involves some extra steps. The sample weights used to fit the final model must be adjusted to reflect the age adjustment. Although alternative approaches could be developed, at this time, it is recommended that the analysis be performed as follows:
 - For each survey year, sum the sample weights of the records in each of the age categories used to compute the age-adjusted rates. This produces for each year and age category, an "estimated" population count.
 - For each year and age category, compute an adjustment factor by dividing the "standard" population count (those previously used to compute the age-adjusted rates) by the corresponding estimated population count. This will produce one adjustment factor for each age category and year.
 - For each record, compute an "adjusted" sample weight by multiplying the record's original sample weight by the adjustment factor that corresponds to the record's age category and survey year.
 - Using the adjusted sample weights, proceed to fit the joinpoint model that was identified by NCI's Joinpoint software ([Appendix IV](#)).
- If a logistic model is being fit to the trend, it is recommended that the point estimates used as input to the Joinpoint software be transformed to the log-odds scale ([Issue 8](#) and [Appendix VI](#)).
- If covariates will be included in the final joinpoint model, it may be desirable to use predictive means and their standard errors as input to NCI's Joinpoint software ([Issue 9](#)).

Joinpoint regression analyses for aggregated survey data

If the trend analysis involves aggregated survey data because record-level data are unavailable or it is not feasible to conduct a record-level analysis, then NCI's Joinpoint software may be used to identify the number and location of joinpoints, and to estimate the slopes and tests of hypotheses, but a statement about the limitations of this approach must be provided ([Issue 5](#)).

Joinpoint regression analyses for vital records data

The full range of estimation and hypothesis testing procedures provided by NCI's Joinpoint software is appropriate for NCHS vital records data ([Issue 6](#)). Therefore, when conducting a trend analysis using vital records data, the number and location of joinpoints and the slope estimates and hypothesis tests for the trend model can be obtained from NCI's Joinpoint software.

Joinpoint model selection when hypothesis tests indicate no change in slope for adjacent line segments

Sometimes the slopes of two adjacent line segments in the model selected by NCI's Joinpoint software are not significantly different according to the *t*-test of the difference. Typically this only happens when the difference between the two slopes is small and not of public health importance. When this happens, the analyst may be tempted to remove the joinpoint between the two line segments and refit the reduced model to facilitate description of the trend. However, the decision to retain or remove the joinpoint depends on whether the trend analysis involves aggregated or record-level data. The NCI Joinpoint software developers are working on a number of modifications that should reduce this problem.

When analyzing aggregated vital records or aggregated survey data (where a subsequent record-level analysis is not feasible), typically hypothesis tests of the difference between the slopes of adjacent line segments are conducted using NCI's Joinpoint software. When this is the case, all joinpoints identified by NCI's Joinpoint software should be

retained regardless of the results of the tests. The developers of the Joinpoint software state that, for a number of reasons, the software's search algorithm (e.g., permutation, Bayesian Information Criterion [BIC]) should be relied on to identify the joinpoints, not the *t*-tests of the difference between slopes of adjacent line segments (see NCI's Joinpoint FAQ: <https://surveillance.cancer.gov/joinpoint/faq/slopes.html>). When using NCI's Joinpoint software, it is not possible to remove a specified joinpoint while retaining the other joinpoints, so the model that is identified when there is one fewer joinpoint may have an entirely different set of joinpoints. Therefore, for aggregated data, when adjacent line segments have statistically similar slopes, the joinpoint connecting them should be retained. When describing what happens over the two time periods, describe each segment separately without regard to the *t*-test of the difference between the slopes (See "Description of a Joinpoint Trend" below).

When analyzing record-level survey data, hypothesis tests of the difference between the slopes of adjacent line segments are conducted using survey analysis software. In contrast to the recommendation for aggregated data, if the survey analysis software determines that the slopes of two adjacent line segments are not statistically significantly different, removing the joinpoint connecting them and fitting the reduced model (using the survey analysis software) is recommended. This can be justified because: a) NCI's Joinpoint software does not fully incorporate all aspects of the complex survey design and thus, its search algorithm may not have "accurately" specified the number and location of the joinpoints and b) with survey analysis software, the analyst specifies the model to be fit, so the "nonsignificant" joinpoint can be omitted and all other joinpoints retained.

Assessing the last observed time point

One cannot look at the data for a single observed time point and say definitively that it represents a new trend if it differs significantly from data values for previous time points as it may be an outlier. Nonetheless, the goal of a trend

analysis may be to assess whether or not the most recently observed time point is consistent with the linear trend previously identified for the preceding time period. For example, suppose the trend during 2000–2014 was previously assessed and a joinpoint identified at 2010. Now the trend for 2000–2015 will be assessed, and the analyst wants to determine whether the 2015 data point is consistent with the 2010–2014 trend. One approach for assessing the last observed time point is to fit a joinpoint model to the extended time period (e.g., to 2000–2015), parameterized to include the joinpoints previously identified for the trend (e.g., 2010, the joinpoint previously identified for 2000–2014) and to include a new joinpoint at the next-to-last observed time point (e.g., 2014). This model would be fit using an appropriate regression procedure (e.g., a regression procedure in a survey analysis software if the data are record-level survey data). If the slope of the final two time point segments differs from that of the preceding line segment, then a deviation from the previous trend may be indicated (e.g., if the slopes for 2014–2015 and 2010–2014 differ). An alternative approach would be to ignore the joinpoints identified for the prior trend and use NCI's Joinpoint software to identify the joinpoints for the extended trend and see if one of them is located at the next-to-last observed time point. With both of these approaches, the power to detect a change in trend when there are only two observed time points in the ending line segment tends to be low; thus, a potential change in trend may be missed. Adding an additional year of data to the time trend also may impact the estimated location of previously identified joinpoints.

Describing a joinpoint trend

The line segments of a joinpoint regression model connect at the joinpoints; a description of a trend that includes references to the trend's line segments should reflect this. Specifically, describe the first line segment as beginning at the first observed time point and extending to the first joinpoint, the first middle line segment as extending from the first joinpoint to the second

joinpoint (and so on), and the ending line segment as extending from the last joinpoint to the last observed time point. For example, if a trend analysis includes data for 1999–2014 and joinpoints are located at 2003 and 2007, then the three segments that comprise the overall trend should be referred to as 1999–2003, 2003–2007, and 2007–2014. It would not be correct to label the second and third line segments as 2004–2007 and 2008–2014 because this would imply that the three line segments do not connect at the joinpoints and that the changes between 2003–2004 and 2007–2008 were not taken into account in the analysis.

The analyst is not required to specify the location of joinpoints when describing a trend; there may be occasions when the analyst wants to acknowledge that a change in trend has occurred, but does not want to identify the specific time point at which the change occurred. For example, if the last observed time point is a preliminary estimate that will be updated or if trends for multiple subgroups are being presented and the trends are similar but have somewhat different estimated joinpoints, a general description (e.g., mortality increased during the early years of the decade, then decreased), may be more appropriate than an explicit description. In addition, there may be occasions when it is desirable to present the confidence limits for the joinpoint locations.

Sometimes as discussed in "Joinpoint model selection when hypothesis tests indicate no change in slope for adjacent line segments," a trend analysis of aggregated data, conducted using NCI's Joinpoint software, will identify a joinpoint, but the *t*-test of the difference between the slopes of the adjacent line segments is not statistically significant. When this occurs, it is recommended that the joinpoint be retained. When describing what happens over the two adjacent time periods, describe each segment separately without regard to the *t*-test of the difference between the slopes. For example, suppose an analysis of a trend from 2006–2016 identifies a joinpoint at 2010. The slope of the 2006–2010 segment is 0.007 ($p = 0.675$) and the slope of the 2010–2016 segment

is 0.020 ($p = 0.002$). The *t*-test of the difference between the two slopes is not statistically significant ($p = 0.148$). The trend would be described as stable from 2006–2010 and increasing from 2010–2016.

Tips on using NCI's Joinpoint program with NCHS data

NCI's Joinpoint software documentation provides guidance on how to use the program and describes the different options, but there are no clear guidelines for choosing the optimal settings for a trend analysis (18). Analytic considerations pertaining to choice of Joinpoint software settings when analyzing NCHS data are discussed below.

NCI's Joinpoint software is revised periodically and a description of the changes made is provided in the online Joinpoint Revision History. When updating to a new version of Joinpoint, users should carefully review the list of changes (bug fixes and new features) to identify any that may impact how an analysis should be specified. For example, addition of the Jump model in Version 4.4.0.0 could impact specification of a mortality trend analysis that spans an ICD code change (see "Known discontinuity (jump) in trend"). As another example, in Version 4.5.0.0, the specification of the minimum and maximum number of observed time points that can be in the beginning, ending, and middle line segments changed (see "Proximity of joinpoints to each other").

The comments and recommendations provided in this report are current with Version 4.5.0.1 and earlier versions of the software.

Input data

Input data for the Joinpoint software are aggregated, not record-level, and include values for the independent variable (the observed time points), the dependent variable (e.g., age-adjusted rates, crude rates, counts, percentages, proportions, and predictive margins), and the estimated standard errors of the dependent variable values. Typically, when analyzing vital records data, rates and their estimated standard errors are

calculated using standard formulas and then input into the Joinpoint software. When analyzing survey data, estimates and their standard errors should be calculated using survey analysis software such as SUDAAN and then input into the Joinpoint software. Covariates cannot be input directly into the Joinpoint software. Therefore, if there are covariates in the model, one analysis approach is to input adjusted point estimates (predictive margins) and their estimated standard errors that have been computed using survey analysis or other software. Another approach that may be feasible if there is only one or a limited number of categorical covariates is to input the covariate as a by-variable; this approach allows pairs of subgroups to be tested to see if the data series are coincident (identical) or parallel. See [Issue 9](#) for a discussion of these two approaches.

Placement of joinpoints on or between observed time points

Joinpoints can be constrained to occur on the observed time points (those for which data are available) or allowed to occur anywhere. Although a better model fit may be obtained if the joinpoints are allowed to fall between observed time points, this generally is not recommended for NCHS data ([Issue 11](#)). To constrain joinpoint locations to occur only at observed time points, use the Grid search method and the default setting of 0 for “Number of points to place between observed x values.”

Known discontinuity (jump) in trend

Sometimes it is known that a discontinuity (or jump) in trend will occur at a particular point in time due to a coding change or other change in comparability. For example, discontinuities in death rate trends occur when there is a change in the revision of the ICD used to code cause of death. Such discontinuities result from a change in scale, not a change in the underlying trend. Sometimes a discontinuity caused by the lack of comparability can be dealt with by limiting the time period included in the trend analysis to time points before or after the coding (or other) change ([Issue 1](#)). But often it is desirable to include in the analysis time points from

before and after a coding change occurs so that a trend of interest can continue to be monitored.

Beginning with Version 4.4.0.0, NCI’s Joinpoint software offers two joinpoint models that accommodate a discontinuity due to a change in scale. The comparability ratio model can be used when comparability ratios have been estimated from a “double-coding” study (e.g., cases have been coded under both the old and new systems) (22). For the comparability ratio model, the Joinpoint software algorithm multiplies the data before the jump by the user-supplied comparability ratio to transform them to the same scale as the data after the jump and a standard joinpoint model is then fit to the transformed data series. Prior to graphing, the transformed data points and fitted values are transformed back to the original scale. An alternative model, the jump model, does not require a user-supplied comparability ratio. For this model, the “jump” is a parameter in the model and is estimated from the data.

The time point at which a jump occurs must be located four or more observed time points from either end of the data. The software developers discuss when to use the comparability ratio model versus the jump model, and specify issues about the results of the jump model when a joinpoint is located near the time point where the jump occurs or when there is a lot of variability in the data (18).

Proximity of joinpoints to each other

The Joinpoint software requires specification of the minimum number of observed time points in the beginning and ending line segments of a trend and in any internal line segments.

For Joinpoint Version 4.4.0.1 and earlier, the value that specifies the minimum number of observed time points included in a beginning or ending line segment includes the single joinpoint in the segment. The lower limit for the minimum number of observed time points that can be specified for the beginning or ending line segment is two (i.e., the beginning or ending time point and the joinpoint); the default setting is three. So, for example, if this minimum is set to two for a trend analysis of annual

data for 1993 through 2014, then the first possible joinpoint location is 1994 and the last possible joinpoint location is 2013. For internal line segments, the specified number of observed time points includes the two joinpoints on either end of the line segment and any observed time points between them. The lower limit for the minimum number of observed time points in an internal line segment is two (i.e., two adjacent observed time points); the default setting is four (the two joinpoints on either end of the segment and the two time points between them). So, for example, if the default minimum setting of four is used and the trend analysis again includes annual data for 1993 through 2014 with the first joinpoint occurring at 1994, the location of the closest subsequent joinpoint would be 1997.

Beginning with Joinpoint Version 4.5.0.0, while the effective minimum length of the beginning, ending, and internal line segments did not change, the specification of their minimum and maximum lengths did change. As described above, prior to Version 4.5.0.0, the specified segment lengths included the joinpoints; the change implemented with Version 4.5.0.0 is that the segment length specifications no longer include the joinpoints. As a result, the lower limit for the minimum number of observed time points that can be specified for the beginning or ending line segment changed from two to one (this specification continues to allow a minimum line segment of length two, consisting of the beginning or ending time point and an adjacent joinpoint). The default setting for the minimum length of the beginning or ending segment changed from three to two. So, for example, if this minimum is set to one for a trend analysis of annual data for 1993 through 2014, then the first possible joinpoint location would be 1994 and the last possible joinpoint location would be 2013. For internal line segments, because the specified number of observed time points no longer include the two joinpoints on either end of the line segment, the lower limit for the minimum number of observed time points changed from two to zero (this specification allows a line

segment of length two consisting of two joinpoints located at adjacent observed time points). The default setting for the minimum length of an internal line segment changed from four to two; a specification of two allows a line segment of length four consisting of the two joinpoints on either end of the segment and two observed time points between them. So, for example, if the default minimum setting of two is used and the trend analysis again includes annual data for 1993 through 2014 with the first joinpoint occurring at 1994, the location of the closest subsequent joinpoint would be 1997.

When choosing the settings for the minimum number of observed time points in the beginning, middle, and ending line segments, consider that:

- Specifying minimums that are too small may result in fitting a model with more line segments than necessary to characterize the trend (i.e., changes in trend that are too small to be of public health importance are detected and modeled). However, specifying minimums that are too large may either result in missing important changes in trend or allowing outlying points to unduly influence a trend line. The analyst must exercise judgment in avoiding these two complementary errors.
- If there is a need to test whether the last observed time point is consistent with a previous linear trend or whether it represents a change in trend, the minimum number of points in the beginning and ending line segments must be set to allow a line segment of length two including the joinpoint (for Version 4.5.0.0 and later, the minimum would be specified as one; for versions prior to 4.5.0.0, the minimum would be specified as two). In this case, it may be advisable to set the minimum number of observed time points in middle line segments to allow segments of length two (e.g., two adjacent joinpoints) in order to provide maximum flexibility for joinpoint location throughout the trend.
- The statistical power to determine if the slope of a line segment is different from 0 is a function of the length of the line segment—the shorter the line segment, the lower the power.
- If the number of observed time points in a line segment, excluding the joinpoints themselves, is fewer than two, then the Joinpoint software generally will not calculate the standard error for the slope of that line segment or hypothesis tests for that segment. Indeed, if the line segment has only two observed time points (a joinpoint and one other observed time point), the Joinpoint software will never compute the standard error of that line segment. For example, if a joinpoint is found at the next-to-last observed time point, the Joinpoint software provides an estimate of the slope of the final two-point line segment, but not an estimate of its standard error or hypothesis tests involving this slope. This is problematic only for trend analyses of vital records data and aggregated survey data because for trend analyses of record-level survey data, final estimates and hypothesis tests are not obtained from the Joinpoint software but from survey analysis software ([Issue 5](#)).

Number of joinpoints to search for

The Joinpoint software also requires specification of the minimum and maximum number of joinpoints to search for. The default setting for the minimum number of joinpoints to search for is zero. This is the usual choice for the minimum because it fits a straight line, which generally is the initial null hypothesis for the trend. The maximum number of joinpoints that can be searched for is two fewer than the number of observed time points (with an upper limit of nine if the grid search is used). However, generally, the maximum number specified should be smaller than this, if possible, in order to avoid an excessive multiple testing penalty and overfitting. The specification should consider the number of observed time points, the line segment length specifications, and the characteristics of the trend. The joinpoints estimated by the

Joinpoint software for a given maximum number of joinpoints specification may differ from those estimated under a different specification.

The Joinpoint program's default settings for the maximum number of joinpoints to search for are:

- 0 when there are 6 or fewer time points,
- 1 when there are 7–11 time points,
- 2 when there are 12–16 time points,
- 3 when there are 17–21 time points,
- 4 when there are 22–26 time points, and
- 5 when there are 27 or more time points.

Note that these settings allow fewer joinpoints than might be expected based on the default line segment lengths (see “Proximity of joinpoints to each other”). For example, under the software's default settings for the maximum number of joinpoints, the Joinpoint program will not search for 2 joinpoints unless there are at least 12 observed time points, but under the default line segment lengths, it would be possible to find 2 joinpoints when there are as few as 8 observed time points (the 2 joinpoints would be located at time points 3 and 6 if the default beginning and ending line segment length of 3 (specified as 2 for Version 4.5.0.0 and later and as 3 for versions prior to 4.5.0.0), and the default middle line segment length of 4 (specified as 2 for Version 4.5.0.0 and later and as 4 for versions prior to 4.5.0.0) are used). The Joinpoint software uses conservative default settings for the number of joinpoints to search for so that: a) there will be no line segments for which the Joinpoint program cannot estimate the standard error because of short length and b) the joinpoints are not constrained to a very limited number of locations.

It generally is advisable to use the default setting for the maximum number of joinpoints so that a parsimonious model is selected. However, there are analyses for which the default setting is not the most appropriate choice. For example, if there is interest in determining if a joinpoint is located at the next to last observed time point, if there is volatility in the middle of the time period, or if it is important to detect small to moderate changes in trend, then it may be advisable to exceed the default for the maximum number of

joinpoints in order to have flexibility in locating them. Also, if visual inspection of the trend or a nonlinearity assessment indicates more changes in trend than the default maximum would allow, it may be advisable to exceed the default maximum. Note that if the default for the maximum number of joinpoints is exceeded, then reducing the spacing between joinpoints may be necessary to allow the Joinpoint program to search for that maximum number. If the specified maximum number of joinpoints for which to search is larger than feasible given the number of observed time points and the specified minimum line segment lengths, the Joinpoint software will generate an error message.

Consider the following when choosing the setting for the maximum number of joinpoints to search for:

- If polynomial regression or orthogonal polynomial contrasts indicated that the trend is nonlinear, consider using those results when setting the maximum number of joinpoints to search for. For example, if polynomial regression or orthogonal polynomial contrasts find a significant quadratic term, consider searching for 1 joinpoint (this would require overriding the software's default if the number of observed time points is fewer than 7 or more than 11). Alternatively, given the imperfect correspondence between the statistically significant degree of a polynomial regression model and the number of joinpoints in a joinpoint regression model (see "Assessing nonlinearity in a trend" in [Issue 7](#)), if there are 12 or more observed time points, consider searching for the default number of joinpoints (e.g., search for 2 if there are 12–16 observed time points).
- The Joinpoint software performs multiple tests to select the optimum number of joinpoints. If the permutation method is used for model selection, adjustment for multiple testing is accomplished using a Bonferroni-type approach directly based on the maximum number of joinpoints specified, so the significance level of each

individual test decreases as the maximum number of joinpoints increases. If the BIC method is used, the likelihood is penalized for the maximum number searched for.

- Specifying a maximum number to search for larger than the default may result in fitting a model with more line segments than necessary to characterize the trend (i.e., joinpoints may be detected but the differences between the slopes of some adjacent line segments may not be statistically significant, or even if they are statistically significant, they may be too small to be of public health importance). However, specifying a maximum that is too small may result in fitting a model with fewer line segments than necessary to characterize the trend. Note that failure to find a significant difference between the slopes of two adjacent line segments does not necessarily indicate that the fitted model has too many line segments; among other things, it may indicate lack of power to detect the difference.
- For the analysis of vital records data, specifying a maximum number of joinpoints to search for that is larger than the default and specifying minimum line segment lengths smaller than the default lengths increases the likelihood that the selected joinpoint model will have line segments for which the standard error of the slope cannot be computed. For the analysis of record-level survey data, this is not a problem because Joinpoint estimates of standard error are not correct and the appropriate survey analysis software must be used as a follow-up to the Joinpoint software analysis.
- The maximum number of joinpoints to search for should be achievable given the number of observed time points and the segment length specifications.

Algorithm used to select the joinpoint model

Currently, the Joinpoint software offers three methods for selecting the joinpoint model (the number and location

of joinpoints): the permutation test, the BIC test, and a modified BIC test (not recommended for analyses of NCHS data because its purpose is to facilitate selection of joinpoints between observed time points). A fourth test, BIC3, will be available soon.

The permutation test, unlike the BIC tests, relies on the asymptotic exchangeability of the residuals. The exchangeability assumption may not hold if the number of observed time points in the trend analysis is not large enough, the analysis includes time points from more than one survey design period (and variances for one design period differ from those for the other design period), or there is year-to-year correlation (due to resampling of PSUs or because the input data are predictive margins). The BIC test and modified BIC test detect smaller changes in trends than the permutation test detects, with the result that the BIC procedures tend to select more joinpoints (sometimes too many) than the permutation procedure. The BIC3 test has a larger multiple-testing penalty than the BIC test and as a result, tends to select fewer joinpoints than the BIC test (sometimes too few are selected), and performs somewhat like the permutation test. When BIC3 is added to the Joinpoint software, an optional procedure also will be added that determines which of the two BIC tests (BIC or BIC3) is optimal for the trend analysis and then uses that test to select the joinpoint model. Both the BIC3 test and the optional procedure may prove useful for NCHS trend analyses.

Because the permutation and BIC tests use different algorithms to estimate 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. While there are no clear guidelines for choosing between the permutation test and the BIC test, the analyst may consider the following when deciding which test to use:

- If there are 10 or more observed time points in the trend analysis, consider using the permutation test to estimate the number and location of joinpoints.

- If there are fewer than 10 time points and the number of observations in the record-level data is sufficiently large for a normality assumption, consider using the BIC test to estimate the joinpoints.
- If the exchangeability assumption of the permutation test may not hold (e.g., when the input data are predicted margins), consider using the BIC test.
- If it is important to detect small changes in trend, consider using the BIC test.

Because the permutation and BIC tests can produce different joinpoint solutions and it is not always clear which test is optimal for the trend analysis, there may be times when the analyst chooses to use both tests and compare the resulting models. When this is done, the solutions from both tests should be presented. If the tests' joinpoint solutions differ, the analyst may also wish to present the confidence limits for the estimated joinpoints (produced by the Joinpoint software); knowing whether or not they overlap can inform assessment of the differences in the solutions.

Linear or log-linear model specification

The Joinpoint software can fit both linear and log-linear models. The slopes of the line segments obtained from a linear model estimate the annual absolute change; the slopes obtained from a log-linear model can be used to estimate the annual percent change (computed as $100 * (\exp(\beta) - 1)$). One motivation for using the log-linear model is that the annual percent change is a metric comparable across subgroups or outcomes with very different rates. For example, a rare cause of death and a common cause of death may change at the same annual percent per year, but it is highly unlikely that they would change the same absolute amount per year (Issue 6).

Logistic model

The Joinpoint software only allows the user to specify a model on a linear or log-linear scale, not on a log-odds scale. When a trend analysis involves a binary outcome variable and use of a

logistic regression model, searching for joinpoints using data on the log-odds scale is more appropriate than searching using data on a linear or log-linear scale (Issue 8). To accomplish this, transform the proportions (or predictive margins if the trend model includes covariates) and their standard errors prior to inputting them into the Joinpoint software and then specify a linear model in the Joinpoint software (see Appendix VI).

Year-to-year correlation

The default assumption of the Joinpoint software is that there is no year-to-year correlation in the data. This is assumed to be true for vital records data (Issue 6), but as discussed in Issue 5, this is not true for some NCHS surveys. It is possible in the Joinpoint software to opt to "Fit an auto-correlated errors model" (either specifying the amount of auto-correlation or having the Joinpoint software estimate it), but this is not recommended when analyzing NCHS survey data because the year-to-year correlation in NCHS surveys has not been quantified and Joinpoint software was not designed to estimate correlation resulting from the reuse of PSUs; adjusting for correlation, especially when there is none, can seriously reduce the power to detect joinpoints. Another source of year-to-year correlation is the use of predictive margins to adjust for covariates; the predictive margins are correlated because they are all estimated from the same regression model. This correlation will impact the algorithm used to search for joinpoints, particularly the permutation test algorithm. At this time, it is not known to what extent the search algorithm might be impacted.

Covariates

Covariates cannot be directly input into the Joinpoint software. However, they can be indirectly considered if included as "by-variables." When a variable is listed as a "by-variable," the trends for two subgroups (e.g., males and females) can be compared to determine if they are coincident (identical) or parallel (37). Alternatively, covariates can be incorporated using predictive margins and their standard errors as the input data. This latter approach does introduce

year-to-year correlation. For a fuller discussion of covariates, see Issue 9. Also see "Year-to-year correlation" above.

Details of joinpoint regression that must be included in a report

When NCI's Joinpoint software is used, specify the version used and list the maximum number of joinpoints searched for; the minimum number of observed time points allowed in the beginning, ending, and middle line segments (if only one joinpoint is searched for, specification of the minimum number of time points in the middle line segment is unnecessary); the type of dependent variable analyzed; the heteroscedastic error option and the search and model selection methods used; and the overall alpha level. Also specify whether a log transformation was applied, any auto-correlation that was used, and any special features used, such as the "jump" option or an auto-correlated errors option. For example, the statement could include the wording:

"NCI's Joinpoint software (Version 4.5.0.1) was used to fit weighted least-squares regression models to the estimated proportions on the linear scale. Allowing as few as two observed time points in the beginning, ending, and middle line segments (including the joinpoints), a maximum of two joinpoints were searched for using the Grid search algorithm and the BIC test and an overall alpha level of 0.05."

Guideline 12

- If the data are record-level survey data, NCI's Joinpoint software may be used to estimate the joinpoints for a nonlinear trend, and then survey analysis software used to fit and test the indicated joinpoint model. If the slopes of two adjacent line segments in the fitted joinpoint regression model are not statistically significantly different (based on the hypothesis tests obtained from the survey analysis software), consider dropping the joinpoint between them and refit the reduced model (using the survey analysis software). Provide a rationale.

- b. If the data are vital records data or aggregated survey data, NCI's Joinpoint software can be used to obtain slope estimates and tests of hypothesis for a straight line (a zero joinpoint model) or for a joinpoint model. Even if the difference between the slopes of two adjacent line segments in the model selected by the Joinpoint software is not statistically significant, generally report the model with all identified joinpoints and describe the two segments separately without regard to the *t*-test of the difference between the slopes.
- c. If a goal of the trend analysis is to assess whether the final observed time point represents a change in the trend, joinpoint regression can be used to make this assessment. One approach is to extend a previously identified joinpoint regression model to include the last observed time point and specify a new joinpoint at the next-to-last observed time point. Another approach is to use NCI's Joinpoint software to fit a new joinpoint regression model to the extended time period (with the default spacing between joinpoints overridden so that a joinpoint can occur at the next-to-last observed time point). For record-level data, any such model identified using NCI's Joinpoint software would subsequently be fit and tested using survey analysis software.
- d. When describing the trend associated with a joinpoint regression model and specifying the line segments, refer to the beginning line segment as extending from the first observed time point through the first joinpoint, the first middle line segment as extending from the first joinpoint through the second joinpoint (and so on), and the ending line segment as extending from the last joinpoint to the last observed time point. For some trends, it may be more appropriate to provide a more general description of the trend and to present the confidence limits of the joinpoint locations.
- e. Generally, use the Grid method to search for joinpoints and specify that no joinpoints be located between observed time points.
- f. Review carefully the analytic considerations before choosing the settings for the minimum and maximum number of joinpoints to search for and the settings for the minimum number of observed time points in the beginning and ending line segments or the middle line segments. The default settings are not always the most appropriate choice. For example, the default settings may not be appropriate if a significant polynomial term was identified in the nonlinearity assessment. In this case, consider overriding the software default setting for the maximum number of joinpoints to search for to reflect this and consider specifying minimum line segment lengths less than the defaults to allow flexibility in joinpoint location. If there is interest in determining if a joinpoint is located at the next to last observed time point or, if there is interest in assessing volatility in the middle of the time period, then the minimum number of observed time points in the beginning, ending, and middle line segments should be set to allow maximum flexibility.
- g. For trend analyses with 10 or more time points, consider using the permutation test for model selection. If there are fewer than 10 time points but the samples are large or predictive margins are the input data, consider using the BIC criterion for model selection. Analytic considerations may indicate a different test choice.
- h. Do not fit joinpoint regression models using the auto-correlation options of the Joinpoint software.
- i. When logistic regression is used to model a trend in a binary outcome variable, transform the proportions (or predictive margins) and their standard errors to the log-odds scale prior to inputting them into the Joinpoint software. Then specify a linear model for the Joinpoint program run. If covariates will be included in the final joinpoint model, consider using predictive margins and their standard errors as input to NCI's Joinpoint software. If age-adjusted rates computed using standard population counts applied to record-level survey data are the input data for NCI's Joinpoint software, fit the final joinpoint model using sample weights adjusted for the standard population counts.
- j. When describing the joinpoint analysis, list the maximum number of joinpoints searched for, the minimum number of observed time points allowed in the beginning, ending, and middle line segments (if only one joinpoint is searched for, specification of the minimum number of time points in the middle line segment is unnecessary), the type of dependent variable analyzed, the heteroscedastic error option and the search and model selection methods used and the overall alpha level, whether a log transformation was applied, any auto-correlation that was used, and any special features used. See above for suggested wording.

Illustrative Examples of Trend Analysis

This section presents examples of trend analyses from three NCHS surveys and from vital records data that were conducted explicitly for this report. The analyses follow the guidelines presented in this report and are intended to be illustrative rather than substantive. The first example uses NHIS to assess trends in emergency room use among adults aged 18–64 during 2000–2015, by health insurance status. The second example is from NHANES and assesses the trend in the prevalence of obesity among children and youths aged 2–19 years during 1988–2014. The third example, from National Hospital Ambulatory Medical Care Survey (NHAMCS), examines trends in electrocardiogram use during emergency department visits. The final example assesses trends in teen births during 1991–2015.

Example A. Emergency Room Use Among Adults Aged 18–64, by Insurance Status: NHIS, 2000–2015

This example uses record-level data on self-reported emergency room use during the past 12 months and health insurance coverage at the time of interview from the 2000–2015 NHIS. Emergency room use data were collected using the following question: “During the past 12 months, how many times have you gone to a hospital emergency room about your own health, (this includes emergency room visits that resulted in a hospital admission)?” and was recoded as a binary variable: any emergency room use (1) or no emergency room use (0). Multiple types of insurance coverage may be reported in NHIS; in this analysis, insurance coverage was recoded to be mutually exclusive in a hierarchy—any private coverage, Medicaid coverage (includes “other public” or Children’s Health Insurance Program [CHIP] coverage), or uninsured. Approximately 4% of the population aged 18–64 does not fall into one of these three categories (minimum: 2.6% in 2002, maximum: 4.8% in 2013).

Research question

How has emergency room use among adults aged 18–64 with private coverage, Medicaid coverage, and no health insurance coverage changed during 2000–2015?

Time period of the analysis

As advised in Guideline 1, the following rationale for the choice of the time period for the analysis is provided. The first observed time point in the analysis was the 2000 NHIS survey year, the beginning of a new century. The time period of the analysis extended through 2015, the most recent data available at the time of the analysis, because recent trends were of interest. This time period includes the passage of the Affordable Care Act (ACA) in 2010 and is prior to full implementation of the ACA’s provisions, which could potentially affect emergency room use. The data collected during these years are comparable as advised in Guideline 1.

Observed time points included in the analysis

The observed time points are the 16 equally spaced data years, 2000 through 2015. All of the 16 annual estimates of emergency room use in the covered time period were used in the trend analysis, as advised in Guideline 2.a. No pooling across years occurred, as advised in Guideline 3.a. For the nonlinearity assessment and the regression procedures, the time variable (year) was scaled to the values 0–15 (i.e., 0 = 2000, ..., 15 = 2015). Note that this scaling is possible because the time points are equally spaced (Guideline 4.a.).

Data source and type of data

The data are from a complex survey, NHIS, and are analyzed as record-level data (Guideline 5.a.).

Analysis approach

Because NHIS is a complex survey, record-level data were used with survey analysis software to obtain the annual estimates and their standard errors and for an initial assessment of nonlinearity in the trend using orthogonal polynomial contrasts (Guidelines 5.a. and 7.b.). For ease of interpretation, linear regression models were used to model the trends in the binary outcome variables (Guideline 8.b.). All of the predicted values for the observed time points were found to be within the unit interval, which affirmed the appropriateness of using a linear model (Guideline 8.b.). Aggregated data were used with NCI’s Joinpoint software to identify the number and location of joinpoints for the insurance groups with nonlinear trends (Guidelines 5.b., 7.c., and 12.a.). Because the data are from a complex survey, final models were fit using the record-level data and survey analysis software to obtain slope estimates and hypothesis tests (Guidelines 5.b. and 12.a.). Specifics are described in Steps 1 through 4 below.

Computer code

SAS and SUDAAN code for this example are provided following the “Conclusions” section. Settings used for NCI’s Joinpoint software are specified in the “Step 3” section.

Step 1. Compute annual survey estimates and plot the data

Annual estimates of the percentage of persons with any emergency room use during the past 12 months and their standard errors were calculated in SUDAAN’s PROC DESCRIPT using the appropriate sample weights and incorporating the complex sample design (Guideline 5.a.) (15).

Table A and Figure 1 show the percentage of persons with any emergency room use during the past 12 months among adults with private, Medicaid, and no health insurance coverage during 2000–2015. The graph shows that there is fluctuation in the estimates, especially for the Medicaid and uninsured groups (possibly due to small sample sizes), but indicates that emergency room use has declined over the time period for all groups. It appears that the declines may have been larger in recent years and based on both prior knowledge and the graph, 2010 is a potential joinpoint.

Step 2. Initial assessment of nonlinearity

For the nonlinearity assessment, the time variable (year) was scaled to the values 0–15 (i.e., 0 = 2000, ..., 15 = 2015) (Guideline 4.a.). The binary insurance coverage variables were scaled as 0 and 100 so as to represent insurance coverage as percentages. Record-level data were used for this analysis. The orthogonal polynomial option (POLY) in SUDAAN’s PROC DESCRIPT was used to test the trends for the three insurance status groups for nonlinearity (quadratic and cubic effects) (Guideline 7.b.) (15,16). The trends for all three insurance groups were found to be nonlinear (Table B). The highest-order statistically significant orthogonal polynomial for the private insurance group was the quadratic contrast; the highest-order statistically significant orthogonal polynomial for the Medicaid and uninsured groups was the cubic contrast. As discussed in Issue 7, the contrasts of lower-order than the highest-order statistically significant contrast are ignored. Because the trends for the three insurance groups were found to be nonlinear, NCI’s Joinpoint

software was used to estimate the number and location of the changes in trend (Guidelines 7.c. and 12.a.). Recognizing that the degree of nonlinearity indicated by the orthogonal polynomial contrast results may not correspond to the number of joinpoints, the Joinpoint software’s default settings for the maximum number of joinpoints to search for were used.

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

Because the orthogonal polynomial contrast analysis indicated that the trends in emergency room use were nonlinear, NCI’s Joinpoint software (Version 4.0.4) was used to fit joinpoint regression models to the trend for each insurance coverage group (Guidelines 5.b., 7.c., and 12.a.). For this analysis, the values 0, ..., 15 were used to represent the observed time points. For each insurance coverage group, the percentages and their standard errors obtained from SUDAAN’s PROC DESCRIPT (Table A) and the recoded year of the estimate (0 to 15) were input into NCI’s Joinpoint program. Weighted least-squares regression was used to fit the joinpoint models.

The following settings were used for the Joinpoint software runs:

- type of estimate = percent,
- linear scale (Guideline 8.b.),
- weighted least-squares,
- Grid search method for detecting joinpoints with no joinpoints allowed to fall between adjacent observed time points (Guidelines 11.a and 12.e.),
- uncorrelated errors model (Guideline 12.h.),
- minimum and maximum number of joinpoints to search for set at the Joinpoint software defaults for 16 observed time points: minimum number of joinpoints = 0, maximum number = 2 (Guideline 12.f.),
- minimum number of observed time points in the beginning and ending line segments (including the beginning or ending joinpoint) = 3, the default setting for this version of Joinpoint (Guideline 12.f.),
- minimum number of observed time points in a middle line segment

Table A. Example A, observed percentage of adults aged 18–64 who reported any emergency room use in the past 12 months, by health insurance status and survey year: United States, 2000–2015

Survey year	Time point value ¹	Private coverage		Medicaid coverage		Uninsured	
		Percent	SE	Percent	SE	Percent	SE
2000	0	17.5	0.33	42.0	1.55	19.8	0.69
2001	1	17.2	0.32	39.6	1.36	19.3	0.68
2002	2	17.4	0.34	40.7	1.36	21.0	0.73
2003	3	17.3	0.35	39.8	1.30	18.3	0.71
2004	4	17.8	0.38	36.5	1.27	19.5	0.71
2005	5	17.1	0.34	40.0	1.30	19.6	0.65
2006	6	17.0	0.43	38.9	1.38	19.2	0.77
2007	7	16.8	0.42	38.0	1.41	20.5	0.81
2008	8	16.8	0.43	39.8	1.57	19.5	0.81
2009	9	16.4	0.41	41.5	1.39	21.6	0.84
2010	10	17.2	0.40	39.8	1.23	21.5	0.73
2011	11	15.5	0.35	37.7	1.18	21.1	0.72
2012	12	14.9	0.37	39.7	1.15	18.7	0.72
2013	13	14.0	0.36	37.7	1.15	18.5	0.68
2014	14	14.4	0.39	35.2	1.15	16.6	0.72
2015	15	14.0	0.38	34.8	1.09	18.2	0.92

¹These time values were used in all SUDAAN procedures and in NCI’s Joinpoint software to represent the NHIS survey years.

NOTES: The estimates of the percentages and their standard errors were obtained using record-level data and SUDAAN’s PROC DESCRIPT. SE is standard error. NCI is National Cancer Institute.

SOURCE: NCHS, National Health Interview Survey, 2000–2015.

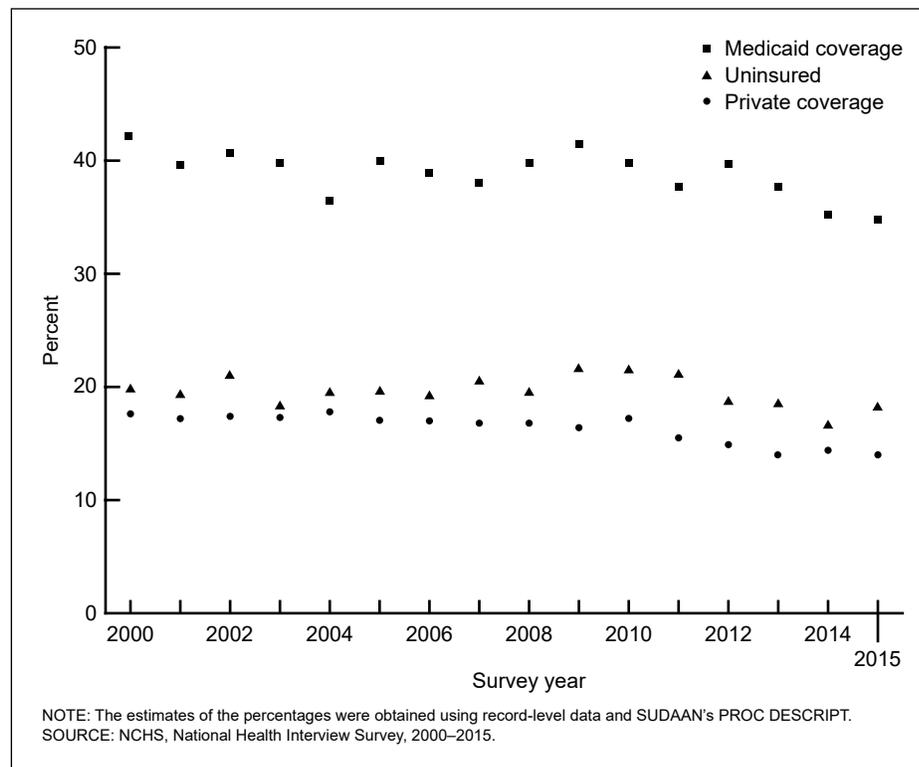


Figure 1. Example A, observed percentage of adults aged 18–64 with any emergency room use in the past 12 months, by health insurance status and survey year: United States, 2000–2015

- (including the joinpoints on each end of the line segment) = 4, the default setting for this version of Joinpoint (Guideline 12.f.), and
- permutation test as the model selection method (Guideline 12.g.), with an overall significance level of alpha = 0.05 and the number of randomly permuted data sets to the default (n = 4,499).

Table B. Example A, orthogonal polynomial contrast assessment of nonlinearity of trends in emergency room use in the past 12 months among adults aged 18–64, by health insurance status: United States, 2000–2015

Health insurance status	P values for orthogonal polynomial contrasts		
	Linear contrast	Quadratic contrast	Cubic contrast
Private coverage	0.000	0.000	0.900
Medicaid coverage	0.000	0.179	0.001
Uninsured	0.055	0.001	0.007

0.000 quantity more than zero but less than 0.0005.

NOTE: Tests of orthogonal polynomial contrasts were obtained using SUDAAN's PROC DESCRIPT.

SOURCE: NCHS, National Health Interview Survey, 2000–2015.

As shown in [Table C](#), NCI's Joinpoint program found joinpoints in 2010 and 2013 for privately insured adults, no joinpoints for adults with Medicaid, and a joinpoint in 2010 for uninsured adults. Shown for illustrative purposes, are the slopes of the line segments obtained from NCI's Joinpoint software and the *p* values for the tests that those slopes are zero. However, because the data are survey data, these estimates are not used to describe or evaluate the trends and would not be included in a report of this analysis (Guidelines 5.b. and 12.a.). Note that the number of joinpoints identified by NCI's Joinpoint software for each of the three groups may appear to be inconsistent with the nonlinearity assessments obtained from the orthogonal polynomial contrasts. For example, the orthogonal polynomial contrast assessment indicated a cubic trend for the uninsured group,

but the Joinpoint software identified only one joinpoint. As discussed in [Issue 12](#), such inconsistencies are not unexpected. Inconsistencies may reflect differences in how the methods assess nonlinearity or limitations in joinpoint selection resulting from the Joinpoint settings used (e.g., the minimum number of observed time points in a beginning, ending, or middle line segment limits which time points can be selected as joinpoints).

Step 4. Obtaining final slope estimates and tests of trend

The results of NCI's Joinpoint software analyses (obtained in Step 3) were used to parameterize the final trend models for the three insurance groups and SUDAAN's PROC REGRESS was used to fit these models to the record-level data (Guidelines 5.b. and 12.a.). Again, the values 0, ..., 15 were used to represent the observed time points for

this analysis. For the private insurance group, a joinpoint regression model with joinpoints at 2010 and 2013 was fit ([Figure 2](#)). For the Medicaid group, a linear regression model was fit and for the uninsured group, a joinpoint regression model with a joinpoint at 2010 was fit ([Figures 3 and 4](#)). The slopes generally resemble those obtained from the Joinpoint software, but the *p* values for tests of statistical significance generally are smaller than those obtained from the NCI Joinpoint software run, resulting in more departures from the null hypothesis ([Table C](#)). Per Guidelines 5.b. and 12.a., the slope estimates and tests of significance from the SUDAAN runs are used to evaluate the trends, not those from NCI's Joinpoint software.

For adults with private insurance, the slopes for the first two line segments (2000–2010 and 2010–2013) were negative and statistically significantly different from zero, indicating decreasing emergency room use during both time periods. The third slope (2013–2015) was not statistically significantly different from zero, indicating that emergency room use was stable during this time period. The slopes for the first two time periods were statistically significantly different from each other, indicating that emergency room use declined more rapidly during 2010–2013 than during the earlier period. The difference between the second and third slopes was also

Table C. Example A, parameter estimates for joinpoint regression models fit to trends in emergency room use in the past 12 months among adults aged 18–64, by health insurance status: United States, 2000–2015

Health insurance status and joinpoint regression model line segments	Parameter estimates for joinpoint model fit by NCI's Joinpoint software ¹			Parameter estimates for joinpoint model fit by SUDAAN using NCI Joinpoint software-identified joinpoints ²			
	Slope	SE	P value of test that slope = 0	Slope	SE	P value of test that slope = 0	P value of test for change in slope
Private coverage (2 joinpoints: 2010, 2013)							
2000–2010	–0.082	0.029	0.022	–0.082	0.035	0.020	1v2: 0.000 2v3: 0.004
2010–2013	–0.893	0.360	0.038	–0.879	0.122	0.000	
2013–2015	0.065	0.385	0.869	0.045	0.232	0.847	
Medicaid coverage (0 joinpoints)							
2000–2015	–0.278	0.092	0.009	–0.302	0.073	0.000	...
Uninsured (1 joinpoint: 2010)							
2000–2010	0.168	0.111	0.158	0.188	0.068	0.006	1v2: 0.000
2010–2015	–0.797	0.333	0.036	–0.799	0.150	0.000	

0.000 quantity more than zero but less than 0.0005.

... Not applicable.

¹NCI's Joinpoint software (Version 4.0.4) was run with a minimum of three observed time points in the beginning and ending line segments (including the joinpoint), and a minimum of four observed time points in a middle line segment (including the two joinpoints). A maximum of two joinpoints were searched for using the Grid search algorithm, the permutation test, and an overall alpha level of 0.05.

²Joinpoint regression model was fit using SUDAAN's PROC REGRESS and the joinpoints identified by NCI's Joinpoint software.

NOTES: NCI is National Cancer Institute. SE is standard error.

SOURCE: NCHS, National Health Interview Survey, 2000–2015.

significant, reflecting the end of the decline in emergency room use. Note that the line segments of the trend are referred to as 2000–2010, 2010–2013, and 2013–2015 (as specified in 12.d.); it would not be correct to label the second and third line segments as 2011–2013 and 2014–2015 because this would imply that the line segments do not connect at the joinpoints and that the changes between 2010–2011 and 2013–2014 were not taken into account in the analysis.

For adults with Medicaid, the negative slope for 2000–2015, -0.30 percentage points per year, was statistically significantly different from zero, indicating a decreasing trend during this period.

For uninsured adults, the positive slope for the first period, 2000–2010, was statistically significantly different from zero, indicating an increasing trend during this period. The negative slope for the second period (2010–2015) also was significantly different from zero, indicating a decreasing trend during that period. The rates of change in the two periods were significantly different from each other.

Conclusions

The percentage of privately insured adults aged 18–64 with any emergency room use during the past 12 months declined from 2000 through 2013 and remained stable during 2013–2015. Specifically, during 2000–2010, emergency room use among these adults declined at nearly 0.1 percentage point per year and during 2010–2013 it declined more rapidly, at nearly 1 percentage point per year.

Emergency room use among uninsured adults aged 18–64 increased at almost 0.2 percentage points per year during 2000–2010 and decreased at almost 1 percentage point per year during 2010–2015.

Among adults aged 18–64 with Medicaid coverage, emergency room use declined 0.3 percentage point per year throughout the period 2000–2015; there was no change in trend as was observed for the other two groups.

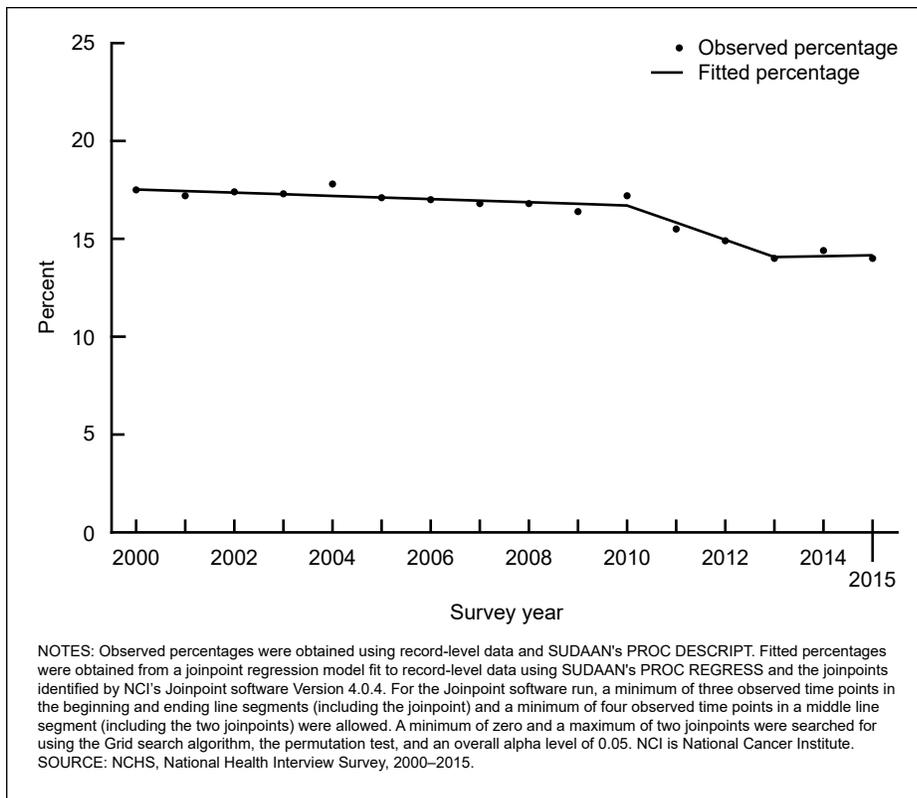


Figure 2. Example A, observed and fitted percentages of adults aged 18–64 with private health insurance coverage who reported any emergency room use in the past 12 months, by survey year: United States, 2000–2015

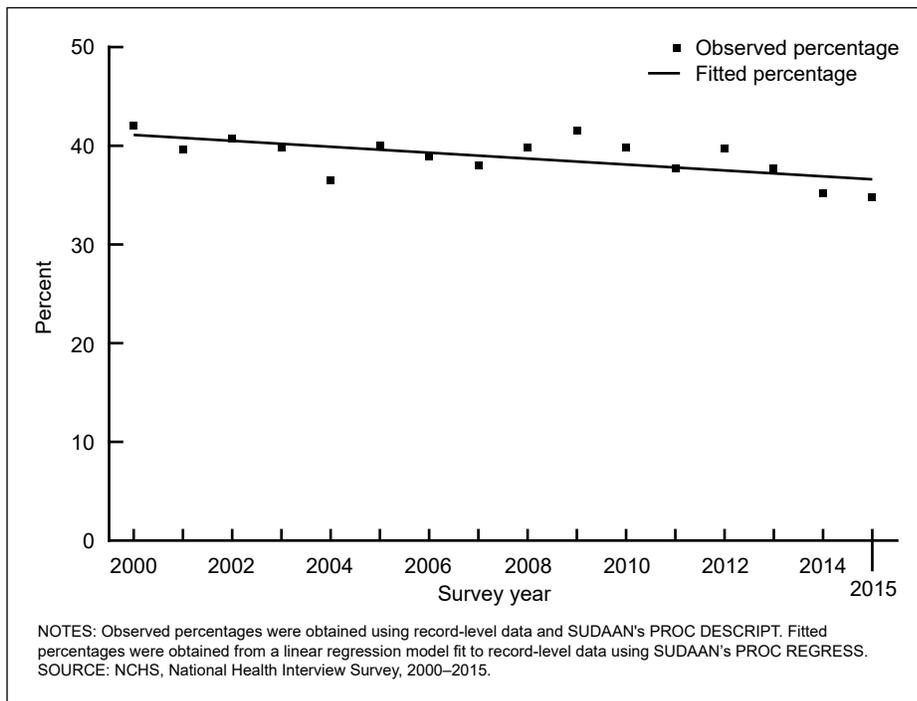


Figure 3. Example A, observed and fitted percentages of adults aged 18–64 with Medicaid coverage who reported any emergency room use in the past 12 months, by survey year: United States, 2000–2015

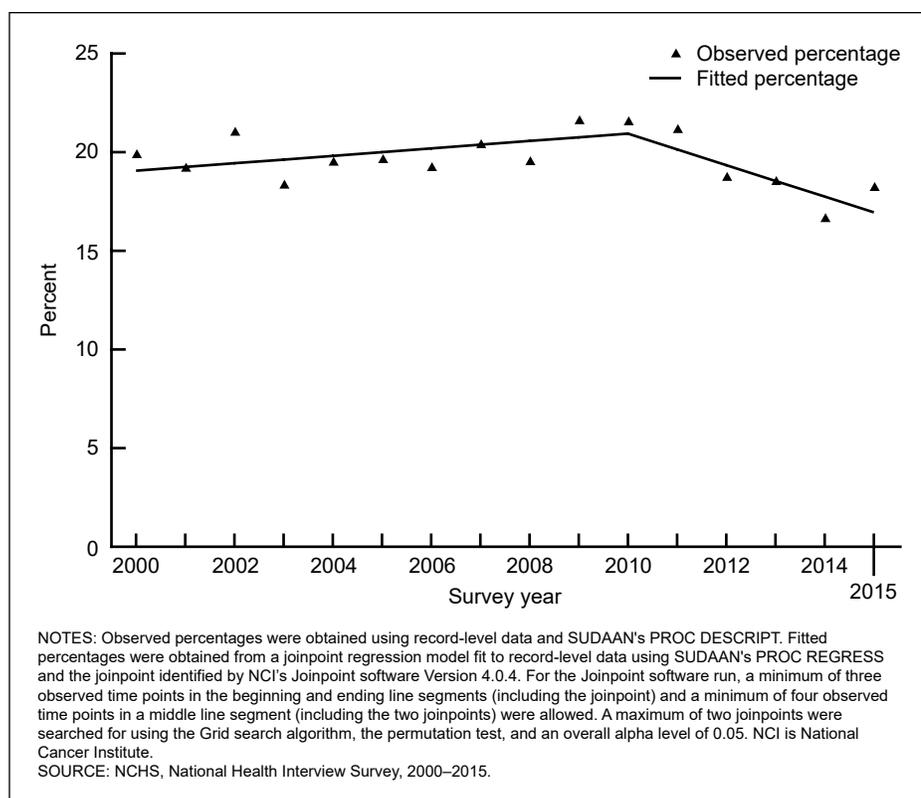


Figure 4. Example A, observed and fitted percentages of adults aged 18–64 with no health insurance coverage who reported any emergency room use in the past 12 months, by survey year: United States, 2000–2015

SAS and SUDAAN code for Example A

SAS and SUDAAN code for Example A is provided below. The variables used in the SAS and SUDAAN code for Example A are shown in [Table D](#).

SUDAAN code for Step 1. Compute annual estimates of the percentage of adults aged 18–64 with an emergency room visit during the past 12 months by insurance group, using SUDAAN's PROC DESCRIPT.

```
PROC SORT DATA = NHIS00_15;
```

```
  BY STRATUM PSU;
```

```
run;
```

```
*CALCULATE ESTIMATES FOR EACH YEAR;
```

```
PROC DESCRIPT DATA = NHIS00_15 FILETYPE = SAS DESIGN = WR;
```

```
  NEST STRATUM PSU / MISSUNIT;
```

```
  WEIGHT WTFA;
```

```
  VAR ANYERUSE;
```

```
  CATLEVEL 1;
```

```
  SUBPOPX STATFLG = 1 AND AGEGRP = 2 AND ANYERUSE IN (1, 2)/NAME = "SAMPLE ADULTS AGED  
    18-64";
```

```
  CLASS TIMEPT;
```

```
  SUBGROUP INSTYPE;
```

```
  LEVELS 3;
```

```
  TABLES TIMEPT*INSTYPE;
```

```
  PRINT NSUM="SAMPLE SIZE" WSUM="POPULATION SIZE" TOTAL="TOTAL" PERCENT="PERCENT"
```

Table D. Example A, variables used in the SAS and SUDAAN code for the National Health Interview Survey trend analysis of emergency room use, by health insurance status: United States, 2000–2015

Variable name	Variable description	Variable values
YEAR	Time variable, original	2000, ..., 2015
TIMEPT	Time variable used in SUDAAN's PROC DESCRIPT and to create variables for PROC REGRESS	0 = 2000 1 = 2001 ... 15 = 2015
STRATUM	Stratum	Various
PSU	Primary sampling unit	Various
WTFA	Sample weight	Various
STATFLG	Variable indicating inclusion in analysis sample	0 = Not in analysis sample 1 = In analysis sample
AGEGRP	Age group	1 = under 18 years 2 = 18 to 64 years 3 = 65 years and over
ANYERUSE	Emergency room use in past 12 months	1 = Yes 2 = No . = Missing
ANYERUSE_B	Emergency room use in past 12 months, binary version	0 = No 1 = Yes . = Missing
ANYERUSE_B100	Emergency room use in past 12 months, binary version rescaled to percent, for use in linear regression	0 = No 100 = Yes . = Missing
INSTYPE	Health insurance group	1 = Uninsured 2 = Medicaid (includes other public and CHIP) 3 = Private coverage 4 = Other insured (about 10%)
JOINTP1	First joinpoint for private insurance group and for uninsured group, identified by NCI's Joinpoint software, with value corresponding to TIMEPT	10 = 2000
JOINTP2P	Second joinpoint for private insurance group, identified by NCI's Joinpoint software, with value corresponding to TIMEPT	13 = 2013
SEG1P	Parameterization for SUDAAN's PROC REGRESS of first line segment of the joinpoint regression model for the private insurance group (using Parameterization B of Appendix IV and joinpoints identified by NCI's Joinpoint software)	Value depends on TIMEPT value: = TIMEPT, if TIMEPT ≤ JOINTP1 = JOINTP1, if TIMEPT > JOINTP1
SEG2P	Parameterization for SUDAAN's PROC REGRESS of second line segment of the joinpoint regression model for the private insurance group (using Parameterization B of Appendix IV and joinpoints identified by NCI's Joinpoint software)	Value depends on TIMEPT value: = 0, if TIMEPT ≤ JOINTP1 = TIMEPT-JOINTP1, if JOINTP1 < TIMEPT ≤ JOINTP2P = JOINTP2P-JOINTP1, if TIMEPT > JOINTP2P
SEG3P	Parameterization for SUDAAN's PROC REGRESS of third line segment of the joinpoint regression model for the private insurance group (using Parameterization B of Appendix IV and joinpoints identified by NCI's Joinpoint software)	Value depends on TIMEPT value: = 0, if TIMEPT ≤ JOINTP2P = TIMEPT-JOINTP2P, if TIMEPT > JOINTP2P
SEG1U	Parameterization for SUDAAN's PROC REGRESS of first line segment of the joinpoint regression model for the uninsured group (using Parameterization B of Appendix IV and joinpoints identified by NCI's Joinpoint software)	Value depends on TIMEPT value: = TIMEPT, if TIMEPT ≤ JOINTP1 = JOINTP1, if TIMEPT > JOINTP1
SEG2U	Parameterization for SUDAAN's PROC REGRESS of second line segment of the joinpoint regression model for the uninsured group (using Parameterization B of Appendix IV and joinpoints identified by NCI's Joinpoint software)	Value varies with TIMEPT: = 0, if TIMEPT ≤ JOINTP1 = TIMEPT-JOINTP1, if TIMEPT > JOINTP1

NOTES: CHIP is Children's Health Insurance Program. NCI is National Cancer Institute.

SOURCE: NCHS, National Health Interview Survey, 2000–2015.

```

SEPERCENT="STANDARD ERROR" /STYLE=NCHS NSUMFMT=F12.0 WSUMFMT=F12.0
PERCENTFMT=F9.1 SEPERCENTFMT=F9.2;
OUTPUT NSUM="SAMPLE SIZE" WSUM="POPULATION SIZE" TOTAL="TOTAL" PERCENT="PERCENT"
SEPERCENT="STANDARD ERROR" / FILENAME = ANYERUSE FILETYPE = SAS REPLACE;
RTITLE "ANNUAL ESTIMATES 2000-2015";
run;

```

SUDAAN code for Step 2. Assess nonlinearity by computing orthogonal polynomial contrasts (linear, quadratic, cubic) using SUDAAN's PROC DESCRIPT.

```

PROC DESCRIPT DATA = NHIS00_15 FILETYPE = SAS DESIGN = WR;
  NEST STRATUM PSU / MISSUNIT;
  WEIGHT WTFA;
  VAR ANYERUSE;
  CATLEVEL 1;
  SUBPOPX STATFLG = 1 AND AGEGRP = 2 AND ANYERUSE IN (1, 2)/NAME = "SAMPLE ADULTS AGED
    18-64";
  CLASS TIMEPT;
  SUBGROUP INSTYPE;
  LEVELS 3;
  POLY TIMEPT = 3 / NAME="LINEAR, QUADRATIC, CUBIC TRENDS OVER TIME";
  RTITLE "PROC DESCRIPT WITH POLY STATEMENT (TEST FOR LINEAR, QUADRATIC, CUBIC TRENDS)";
run;

```

SAS and SUDAAN code for Step 3. Fit the final trend models using SUDAAN's PROC REGRESS. For the private insurance and uninsured groups, fit the joinpoint regression models selected by NCI's Joinpoint software, [Table E](#) shows the values of the variables used to parameterize the joinpoint regression models in SUDAAN. For the Medicaid group, fit a regression model with no joinpoint.

Table E. Example A, values of the variables used to parameterize the final joinpoint models fit using SUDAAN software to the trends in emergency room use in the past 12 months among adults aged 18–64, by health insurance status: United States, 2000–2015

Survey year	TIMEPT	Variables used to parameterize joinpoint models in SUDAAN						
		JOINPT1	JOINPT2P	SEG1P	SEG2P	SEG3P	SEG1U	SEG2U
2000	0	10	13	0	0	0	0	0
2001	1	10	13	1	0	0	1	0
2002	2	10	13	2	0	0	2	0
2003	3	10	13	3	0	0	3	0
2004	4	10	13	4	0	0	4	0
2005	5	10	13	5	0	0	5	0
2006	6	10	13	6	0	0	6	0
2007	7	10	13	7	0	0	7	0
2008	8	10	13	8	0	0	8	0
2009	9	10	13	9	0	0	9	0
2010	10	10	13	10	0	0	10	0
2011	11	10	13	10	1	0	10	1
2012	12	10	13	10	2	0	10	2
2013	13	10	13	10	3	0	10	3
2014	14	10	13	10	3	1	10	4
2015	15	10	13	10	3	2	10	5

SOURCE: NCHS, National Health Interview Survey, 2000–2015.

*Create variables needed for joinpoint models;

```
DATA JPMODEL; SET NHIS00_15;
```

*Create variables needed to fit the joinpoint regression model for the private insurance and uninsured groups. NCI's Joinpoint software identified joinpoints at 2010 and 2013 for the private insurance group and at 2010 for the uninsured group;

*Create a variable to represent the location of the first joinpoint for the private insurance group and the only joinpoint for the uninsured group:

```
JOINPT1 = 10; /* Joinpoint located at 2010*/
```

```
*Create a variable to represent the location of the second joinpoint for the private insurance group;
```

```
JOINPT2P = 13; /*Joinpoint located at 2013*/
```

```
*Create variables to represent the three line segments for the private insurance joinpoint regression model, 2000–2010, 2010–2013, and 2013–2015:
```

```
IF INSTYPE=3 THEN DO; /*SELECT PRIVATE INSURANCE GROUP*/
```

```
  *1ST line segment, private insurance;
```

```
  IF TIMEPT <= JOINPT1 THEN SEG1P = TIMEPT;
```

```
  ELSE SEG1P = JOINPT1; /*If TIMEPT > 10*/
```

```
  *2ND line segment, private insurance;
```

```
  IF TIMEPT <= JOINPT1 THEN SEG2P = 0;
```

```
  ELSE IF (JOINPT1 < TIMEPT <= JOINPT2P) THEN SEG2P = TIMEPT - JOINPT1;
```

```
  ELSE IF TIMEPT > JOINPT2P THEN SEG2P = JOINPT2P - JOINPT1;
```

```
  *3RD line segment, private insurance;
```

```
  IF TIMEPT <= JOINPT2P THEN SEG3P = 0;
```

```
  ELSE IF TIMEPT > JOINPT2P THEN SEG3P = TIMEPT - JOINPT2P;
```

```
END;
```

```
*Create variables to represent the two line segments for the uninsured joinpoint model, 2000–2010 and 2010–2015;
```

```
IF INSTYPE=1 THEN DO; /*SELECT UNINSURED GROUP*/
```

```
  * 1st line segment, uninsured group;
```

```
  IF TIMEPT <= JOINPT1 THEN SEG1U = TIMEPT;
```

```
  ELSE SEG1U = JOINPT1;
```

```
  *2nd line segment, uninsured group;
```

```
  IF TIMEPT <= JOINPT1 THEN SEG2U = 0;
```

```
  ELSE SEG2U = TIMEPT - JOINPT1;
```

```
END;
```

```
run;
```

```
*Run joinpoint regression model for private insurance group (joinpoints located at 2010, 2013):
```

```
PROC REGRESS DATA=JPMODEL FILETYPE=SAS DESIGN=WR;
```

```
  NEST STRATUM PSU / MISSUNIT;
```

```
  WEIGHT WTFA;
```

```
  SUBPOPX STATFLG = 1 AND AGEGRP = 2 AND INSTYPE = 3 AND ANYERUSE IN (1, 2)/NAME = "SAMPLE  
    ADULTS AGED 18-64, PRIVATE";
```

```
  MODEL ANYERUSE_B100 = SEG1P SEG2P SEG3P;
```

```
  CONTRAST 0 -1 1 0 / NAME = "CHANGE IN SLOPE, SEGMENT 1 VS. SEGMENT 2";
```

```
  CONTRAST 0 0 -1 1 / NAME = "CHANGE IN SLOPE, SEGMENT 2 VS. SEGMENT 3";
```

```
  CONTRAST 0 1 0 -1 / NAME = "CHANGE IN SLOPE, SEGMENT 1 VS. SEGMENT 3";
```

```
  RTITLE "*/JOINPOINT REGRESSION FOR PRIVATE INSURANCE (2010, 2013), ER USE= B0 + B1*SEG1 +  
    B2*SEG2 + B3*SEG3";
```

```
  PRINT BETA="BETA" SEBETA="S.E." T_BETA="T:BETA=0" P_BETA="P-VALUE" / tests=all
```

```
    BETAfmt=F8.5 SEBETAfmt=F8.5 P_BETAfmt=F8.5;
```

```
run;
```

```
*Run joinpoint regression model for uninsured group (2010):
```

```
PROC REGRESS DATA=JPMODEL FILETYPE=SAS DESIGWR;
```

```
  NEST STRATUM PSU / MISSUNIT;
```

```
  WEIGHT WTFA;
```

```
  SUBPOPX STATFLG =1 AND AGEGRP = 2 AND INSTYPE = 1 AND ANYERUSE IN (1, 2)/NAME = "SAMPLE  
    ADULTS AGED 18-64, UNINSURED";
```

```
  MODEL ANYERUSE_B100 = SEG1U SEG2U;
```

```
  CONTRAST 0 -1 1 / NAME = "CHANGE IN SLOPE (SEGMENT 1 vs. SEGMENT 2);
```

```
  RTITLE "*/JOINPOINT REGRESSION FOR UNINSURED (2010), ERUSE = B0 + B1*SEG1U + B2*SEG2U";
```

```

PRINT BETA="BETA" SEBETA="S.E." T_BETA="T:BETA=0" P_BETA="P-VALUE" / tests=all
      BETAFMT=F8.5 SEBETAFMT=F8.5 P_BETAFMT=F8.5;
run;

*Run linear regression model for Medicaid group:
PROC REGRESS DATA=NHIS00_15 FILETYPE=SAS DESIGN=WR;
  NEST STRATUM PSU / MISSUNIT;
  WEIGHT WTFA;
  SUBPOPX STATFLG =1 AND AGEGRP = 2 AND INSTYPE = 2 AND ANYERUSE IN (1, 2)/NAME = "SAMPLE
      ADULTS AGED 18-64, MEDICAID";
  MODEL ANYERUSE_B100 = TIMEPT;
  RTITLE "LINEAR REGRESSION FOR MEDICAID, ERUSE = B0 + B1*TIMEPT";
  PRINT BETA="BETA" SEBETA="S.E." T_BETA="T:BETA=0" P_BETA="P-VALUE" / tests=all
      BETAFMT=F8.5 SEBETAFMT=F8.5 P_BETAFMT=F8.5;
run;

```

Example B. Prevalence of Obesity Among Children and Adolescents Aged 2–19 years: NHANES, 1988–1994 Through 2013–2014

This example uses record-level data from the Mobile Examination Center (MEC) exam of NHANES III (1988–1994) and eight cycles of continuous NHANES (1999–2000 through 2013–2014). Height and weight measurements obtained at the MEC exam were used to calculate body mass index (BMI, weight in kilograms divided by height in meters squared, rounded to one decimal place) for each respondent. Respondents whose BMI was at or above the sex-specific 95th percentile on the CDC BMI-for-age growth charts were classified as obese (38). Obesity was examined for children and adolescents aged 2 to 19 years.

Research question

How has the prevalence of obesity among children and adolescents (aged 2–19 years) in the United States changed over the time period 1988–1994 through 2013–2014?

Time period of the analysis

As advised in Guideline 1, the following rationale for the choice of the time period of the analysis is provided. The first observed time point in the analysis is 1988–1994, the 7-year period when NHANES III was conducted. The time period extended through the most

recently available NHANES data at the time of the study (the 2013–2014 cycle). Use of this extended time period allowed exploration of the most recent trends in obesity in the context of longer range trends. A previously published report was the first to investigate trends in prevalence of obesity in this age group during this time period (39). During these years, the data on height and weight were collected using the same standardized procedures (Guideline 1).

Observed time points included in the analysis

The observed time points in this analysis are unequally spaced intervals of unequal length, one 7-year interval for NHANES III (1988–1994) and eight 2-year intervals for the continuous NHANES cycles (1999–2000 through 2013–2014). Estimates for these nine time points were used in the trend analysis, as advised in Guideline 2.a. No pooling across time points occurred, as advised in Guideline 3.a. Because the observed time points for this analysis represent time periods of different lengths (one 7-year period and eight 2-year periods) and are not equally spaced, values that take this into account were chosen to represent the observed time points in the nonlinearity assessment and regression procedures as described in Step 2 (see Guideline 4.b.).

Data source and type of data

The data are from a complex survey (NHANES) and are analyzed as record-level data (Guideline 5.a.).

Analysis approach

A logistic regression model was used to model the trend for the binary outcome variable (Guideline 8.a.). It is likely that a linear model also would have been appropriate for modeling the trend, but the analyst's preference was for a logistic model. Because the data are from a complex survey, record-level data were used with survey analysis software to obtain the obesity prevalence estimates and their standard errors and to fit polynomial regression models to assess nonlinearity in the trend (Guidelines 5.a. and 7.b.). Because nonlinearity in the trend was detected and a goal of the analysis was to identify when changes in trend occurred, aggregated data were used with NCI's Joinpoint software to identify the number and location of possible joinpoints in the trend (Guidelines 5.b., 7.c., and 12.a.). The prevalence estimates and their standard errors were transformed to the log-odds scale before being input into NCI's Joinpoint software (Guidelines 8.a. and 12.i.). Record-level data and survey analysis software were used to obtain final slope estimates and hypothesis tests for the trend (Guidelines 5.b. and 12.a.). Specifics are described in Steps 1–4.

Computer code

SAS and SUDAAN code for this example is provided following the “Conclusions” section. Settings used for NCI’s Joinpoint software are specified in the “Step 3” section.

Step 1: Compute survey estimates and plot the data

Estimates of the prevalence of obesity among children and adolescents and their standard errors were calculated for NHANES III (1988–1994) and the eight 2-year cycles (1999–2000 through 2013–2014) using SUDAAN’s PROC DESCRIPT with the appropriate sample weights and complex survey design incorporated (Guideline 5.a.) (15).

Table F and Figure 5 show the prevalence of obesity among children and adolescents during 1988–1994 through 2013–2014 (expressed as percentages). Figure 5 shows that there is fluctuation in the estimates over time, but indicates that the prevalence of obesity generally increased over some portion of the time period and the trend may have changed in later years.

Step 2: Initial assessment of nonlinearity

Because the observed time points for this analysis represent time periods of different lengths (one 7-year period and eight 2-year periods) and are not equally spaced, values that take this into account must be chosen to represent them (Guideline 4.b). As shown in Table F, values were assigned to the midpoint of each time interval with the values scaled to reflect the length of time between the midpoints (Guideline 4.b.). The midpoint of 1988–1994 is 1991.5, the midpoint of 1999–2000 is 2000, and so forth). Therefore, the value 1 was used for the midpoint of the first interval (1991.5) and the value 9.5 was used for the midpoint of the second interval (2000) because there are 8.5 years between the two midpoints. There are 2 years between the midpoints of the seven remaining time intervals, so the values 11.5 (for 2001–2002) to 23.5 (for 2013–2014) were used.

Because the outcome variable is binary (0 = nonobese, 1 = obese) and the final trend model will be logistic,

Table F. Example B, prevalence of obesity among children and adolescents aged 2–19 years, by survey cycle: United States, 1988–1994 through 2013–2014

Survey cycle	Time point value ¹	Prevalence (percent) ²	SE	Transformed prevalence estimate ³	Transformed standard error ⁴
1988–1994	1.0	10.02	0.54	-2.195	0.060
1999–2000	9.5	13.94	0.86	-1.820	0.072
2001–2002	11.5	15.36	0.94	-1.706	0.072
2003–2004	13.5	17.12	1.26	-1.577	0.089
2005–2006	15.5	15.43	1.35	-1.701	0.104
2007–2008	17.5	16.83	1.29	-1.598	0.092
2009–2010	19.5	16.86	0.71	-1.596	0.051
2011–2012	21.5	16.91	1.01	-1.592	0.072
2013–2014	23.5	17.16	1.09	-1.575	0.077

¹These time values were used in all SUDAAN procedures to represent NHANES III and the NHANES cycles. For the NCI Joinpoint software run, they were multiplied by 10 to eliminate the decimal.
²Prevalence estimates are expressed as percentages (100*p).
³The percentages were rescaled to proportions (p = percent/100) and then transformed to the log-odds scale by applying the formula $\ln(p/(1-p))$ (Appendix VI).
⁴The 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 $se(p)/(p*(1-p))$ (Appendix VI).

NOTES: The prevalence estimates and their standard errors were obtained using record-level data and SUDAAN’s PROC DESCRIPT. SE is standard error. NCI is National Cancer Institute.

SOURCE: NCHS, National Health and Nutrition Examination Survey, 1988–1994 through 2013–2014.

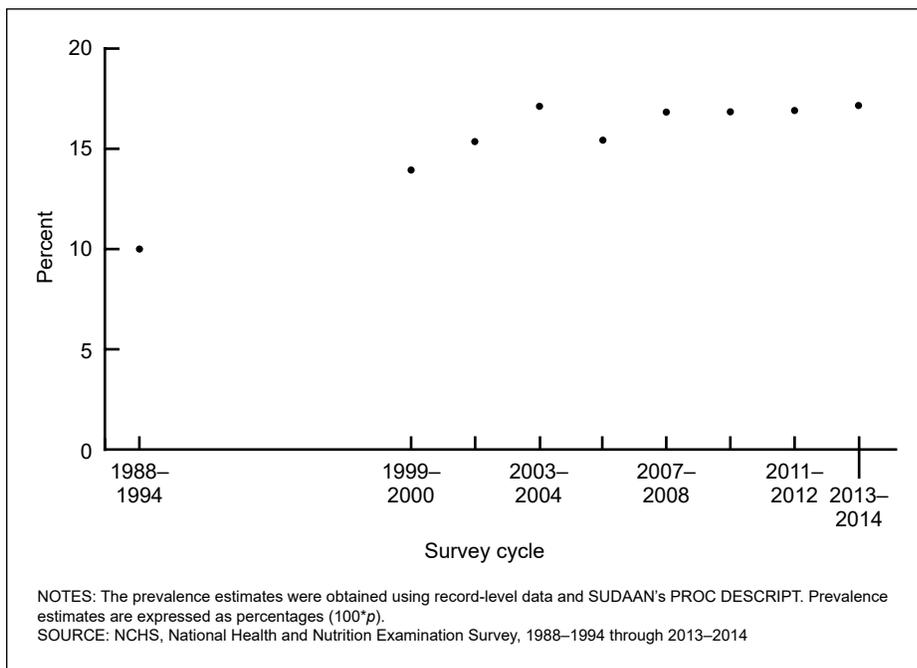


Figure 5. Example B, observed prevalence of obesity among children and adolescents aged 2–19 years, by survey cycle: United States, 1988–1994 through 2013–2014

a logistic regression model with a quadratic time term was fit to assess nonlinearity (with only nine observed time points in the trend analysis, testing for a quadratic effect was deemed sufficient). SUDAAN’s PROC RLOGIST was used to fit a model with both linear and quadratic time terms to the record-level data (Guidelines 7.b. and 8.a.). The quadratic term was statistically

significant, indicating that the trend is nonlinear.

Step 3. Estimate the number and location of joinpoints for the nonlinear trend

Because the polynomial regression analysis indicated that the trend in obesity prevalence is nonlinear with a significant second-order (quadratic) term, the analysts conducted a joinpoint analysis to

Table G. Example B, parameter estimates for joinpoint regression models fit to the trend in obesity prevalence among children and adolescents aged 2–19 years: United States, 1988–1994 through 2013–2014

Joinpoint regression model line segments	Parameter estimates for joinpoint model fit by NCI's Joinpoint software ¹			Parameter estimates for joinpoint model fit by SUDAAN using NCI Joinpoint software-identified joinpoint ²			
	Slope	SE	P value of test that slope = 0	Slope	SE	P value of test that slope = 0	P value of test for change in slope
1988–1994 through 2003–2004	0.046	0.003	0.000	0.045	0.007	0.000	2v1: 0.004
2003–2004 through 2013–2014	0.004	0.005	0.423	0.005	0.008	0.584	

0.000 quantity more than zero but less than 0.0005.
¹NCI's Joinpoint software (Version 4.4.0.0) was run with a minimum of two observed time points in the beginning and ending line segments (including the joinpoint). A maximum of one joinpoint was searched for using the Grid search algorithm, the BIC test, and an overall alpha level of 0.05. For the Joinpoint software run, the obesity prevalence estimates were transformed to the log-odds scale.
²Joinpoint regression model was fit using SUDAAN's PROC RLOGIST and the joinpoint identified by NCI's Joinpoint software.

NOTES: NCI is National Cancer Institute. SE is standard error.
 SOURCE: NCHS, National Health and Nutrition Examination Survey, 1988–1994 through 2013–2014.

search for one joinpoint (Guidelines 5.b., 7.c., and 12.a.). Note that searching for one joinpoint was consistent both with the results of the polynomial regression and with the Joinpoint software default setting. Because logistic regression was being used to model the trend in obesity prevalence, the prevalence estimates and their standard errors obtained from SUDAAN's PROC DESCRIP were transformed to the log-odds scale (Table F and Appendix VI) and the transformed estimates were used as input for NCI's Joinpoint software (Guideline 8.a. and 12.i.). For the Joinpoint software run, the time values (1, 9.5, through 23.5) were modified by multiplying them by 10 to eliminate the decimal.

The analysts input the transformed proportions, their standard errors and values of the observed time points into NCI's Joinpoint software (Version 4.4.0.0), and used weighted linear least-squares regression to determine if there was a joinpoint and if so, its location (Guidelines 5.b., 7.c., and 12.i.). As noted above, searching for a maximum of one joinpoint was consistent both with the results of the polynomial regression and with the Joinpoint software default setting.

The analysts did not use the default settings for the minimum number of joinpoints in the beginning and ending because they wanted to allow maximum flexibility in the location of any joinpoint (Guideline 12.f.). Using the defaults would have restricted the location of the joinpoint to the middle of the time period (2001–2002 through 2009–2010) and precluded identification of a recent change in trend.

The following settings were used for the Joinpoint software (Version 4.4.0.0) run:

- type of estimate = other,
 - linear scale,
 - weighted least-squares,
 - Grid search method for detecting joinpoints with no joinpoints allowed to fall between adjacent observed time points (Guidelines 11.a. and 12.e.),
 - uncorrelated errors model (Guideline 12.h.),
 - minimum and maximum number of joinpoints to search for set at the
- Joinpoint software defaults for 9 observed time points (for Version 4.4.0.0): minimum number of joinpoints = 0, maximum number = 1, (Guideline 12.f.),
 - minimum number of observed time points in the beginning and ending line segments (including the beginning or ending joinpoint) = 2 (Guideline 12.f.),
 - minimum number of observed time points in a middle line segment (including the joinpoints on each end of the line segment) = 4 (Guideline 12.f.), and

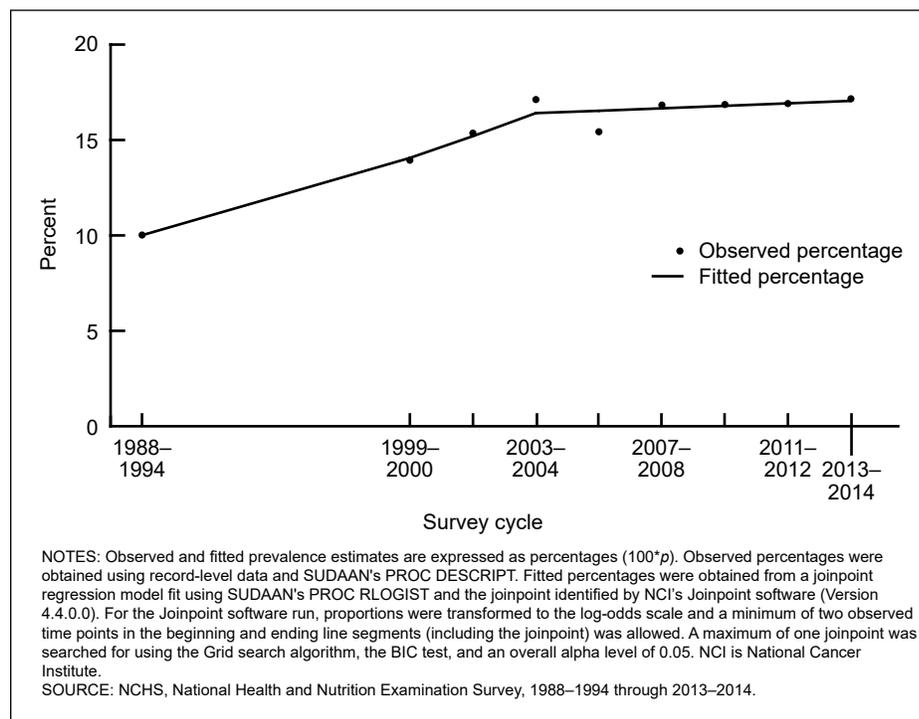


Figure 6. Example B, observed and fitted prevalence of obesity among children and adolescents aged 2–19 years, by survey cycle: United States, 1988–1994 through 2013–2014

- BIC test as the model selection criterion because there are only nine observed time points and it was desirable for the analysis to be sensitive to small changes in trend (Guideline 12.g.). An overall significance level of $\alpha = 0.05$ and the default number of randomly permuted datasets ($n = 4,499$) was used.

As shown in [Table G](#), the Joinpoint program found a joinpoint at the midpoint for the 2003–2004 cycle. Shown for illustrative purposes are the slopes of the line segments obtained from NCI’s Joinpoint software and the p values for the tests that those slopes are zero. However, because the data are survey data, these estimates are not used to describe or evaluate the trends and would not be included in a report of this analysis (Guidelines 5.b. and 12.a.).

Step 4. Obtaining final slope estimates, tests of trend

The final trend model was a logistic regression model with a joinpoint located at the midpoint of the 2003–2004 survey cycle. SUDAAN’s PROC RLOGIST was used to fit this model to the record-level data (Guidelines 5.b. and 12.a.). For this analysis, the time values 1, 9.5, ..., and 23.5 were used.

For children and adolescents aged 2–19 years, the slope (the estimated beta coefficient) for the first line segment (1988–1994 through 2003–2004) was positive and significantly different from zero ([Table G](#) and [Figure 6](#)). The slope for the second line segment (2003–2004 through 2013–2014) was also positive but not significantly different from zero. The two estimates were significantly different from one another. These results indicate that obesity prevalence for this age group increased during the first period, and then was stable during the remaining period. The slopes obtained from NCI’s Joinpoint software and from SUDAAN’s PROC RLOGIST ([Table G](#)) are nearly

identical and the hypothesis test results obtained from the Joinpoint software and from SUDAAN are the same, though the associated p values differ somewhat. The estimates from NCI’s Joinpoint software are provided only for illustrative purposes and would not be included in the presentation of this analysis (Guidelines 5.b. and 12.a.). Note that the line segments of the trend are referred to as 1988–1994 through 2003–2004 and 2003–2004 through 2013–2014 (as specified in 12.j.); it would not be correct to label the second line segment as 2005–2006 through 2013–2014 because this would imply that the line segments do not connect at the joinpoint and that the change between 2003–2004 and 2005–2006 was not taken into account in the analysis.

Conclusion

For children and adolescents aged 2–19 years, the prevalence of obesity increased from 1988–1994 through 2003–2004, and then remained stable from 2003–2004 through 2013–2014.

SAS and SUDAAN code for Example B

SAS and SUDAAN code for Example B is provided below. The variables used in the SAS and SUDAAN code for Example B are shown in [Table H](#).

SAS code to create STRATUM, PSU, and WT2.

*Create stratum, PSU, and sample weight variables;

```
DATA NHANES88_14;
```

*Create STRATUM variable for time trend analysis;

```
IF SURVEYC=1 THEN STRATUM=200 + SDPSTRA6; /* Renumber stratum for NHANES III so they don't overlap
NHANES 1999-2014*/
```

```
ELSE IF 2 <= SURVEYC <= 9 THEN STRATUM=SDMVSTRA; /*NHANES 1999-2014*/
```

*Create PSU variable for trend analysis;

```
IF SURVEYC=1 THEN PSU=SDPPSU6; /* NHANES III */
```

```
ELSE IF 2 <= SURVEYC <= 9 THEN PSU=SDMVPSU; /* NHANES 1999-2014 */
```

*Create sample weights for trend analysis;

```
WT2=.;
```

```
IF SURVEYC=1 THEN WT2=WTPFH6; /* NHANES III MEC + home exam weights for NHANES III */
```

```
ELSE IF 2 <= SURVEYC <= 9 THEN WT2=WTMEC2YR; /*NHANES 1999-2014 2 year MEC weights */
```

SUDAAN code for Step 1. Compute obesity prevalence estimates and their standard errors using SUDAAN’s PROC DESCRIPT.

```
PROC SORT DATA=NHANES88_14;
```

Table H. Example B, variables used in the SAS and SUDAAN code for the National Health and Nutrition Examination Survey trend analysis of obesity prevalence among children and adolescents aged 2–19 years, 1988–1994 through 2013–2014

Variable name	Variable description	Variable values
SURVEYC	Time variable used in SUDAAN's PROC DESCRIPT	1 = NHANES III (1988–1994) 2 = 1999–2000 NHANES cycle 3 = 2001–2002 NHANES cycle 4 = 2003–2004 NHANES cycle 5 = 2005–2006 NHANES cycle 6 = 2007–2008 NHANES cycle 7 = 2009–2010 NHANES cycle 8 = 2011–2012 NHANES cycle 9 = 2013–2014 NHANES cycle
TIMEPT	Time variable used in SUDAAN's PROC RLOGIST	1 = NHANES III (1988–1994) 9.5 = 1999–2000 NHANES cycle 11.5 = 2001–2002 NHANES cycle 13.5 = 2003–2004 NHANES cycle 15.5 = 2005–2006 NHANES cycle 17.5 = 2007–2008 NHANES cycle 19.5 = 2009–2010 NHANES cycle 21.5 = 2011–2012 NHANES cycle 23.5 = 2013–2014 NHANES cycle
TIMEPT_SQ	Quadratic time term used in SUDAAN's PROC RLOGIST	TIMEPT*TIMEPT
SDPSTRA6	Stratum variable for NHANES III, original	Various
SDMVSTRA	Stratum variable for NHANES 1999–2014, original	Various
STRATUM	Stratum variable for trend analysis, generated for all years	Various
SDPPSU6	PSU variable for NHANES III, original	Various
SDMVPSU	PSU variable for NHANES 1999–2014, original	Various
PSU	PSU for trend analysis, generated for all years	Various
WTFHX6	Sample weight for NHANES III, original	Various
WTMEC2YR	Sample weight for NHANES 1999–2014, original	Various
WT2	Sample weight for trend analysis, generated for all years	Various
USEREC	Variable indicating inclusion in analysis sample	1 = In analysis sample . = Not in analysis sample
OBESE	Obesity indicator	1 = Obese 2 = Not obese
OBESE_B100	Obesity indicator, binary version, rescaled to percent, for use in SUDAAN's PROC DESCRIPT and PROC RLOGIST	100 = Obese 0 = Not obese
MEAN	SUDAAN-estimated obesity prevalence, expressed as percent	Various
SEMEAN	SUDAAN-estimated standard error of MEAN	Various
P	SUDAAN-estimated obesity prevalence, expressed as proportion	$P = \text{MEAN}/100$
SEP	SUDAAN-estimated standard error of P	$\text{SEP} = \text{SEMEAN}/100$
LNP	SUDAAN-estimated obesity prevalence, expressed as proportion and transformed to log-odds scale	$\text{LNP} = \text{LOG}(P/(1-P))$
LNSEP	SUDAAN-estimated standard error of SEP, transformed to log-odds scale	$\text{LNSEP} = \text{SEP}/(P*(1-P))$
JOINPT	Joinpoint identified by NCI's Joinpoint software, with value corresponding to TIMEPT	13.5 = 2003–2004 NHANES cycle
SEG1	Parameterization for SUDAAN's PROC RLOGIST of first line segment of the joinpoint regression model (using Parameterization B of Appendix IV and joinpoints identified by NCI's Joinpoint software)	Value depends on TIMEPT: = TIMEPT, if $\text{TIMEPT} \leq \text{JOINPT}$ = JOINPT, if $\text{TIMEPT} > \text{JOINPT}$
SEG2	Parameterization for SUDAAN's PROC RLOGIST of second line segment of the joinpoint regression model (using Parameterization B of Appendix IV and joinpoints identified by NCI's Joinpoint software)	Value varies depends on TIMEPT: = 0, if $\text{TIMEPT} \leq \text{JOINPT}$ = $\text{TIMEPT} - \text{JOINPT}$, if $\text{TIMEPT} > \text{JOINPT}$

NOTES: NHANES is National Health and Nutrition Examination Survey. PSU is primary sampling unit. NCI is National Cancer Institute.

SOURCE: NCHS, National Health and Nutrition Examination Survey, 1988–1994 through 2013–2014.

```

BY STRATUM PSU;
run;
PROC DESCRIPT DATA=NHANES88_14 DESIGN=WR MEANS ATLEVEL1=1 ATLEVEL2=2 NOPRINT;
  NEST STRATUM PSU / MISSUNIT;
  WEIGHT WT2;
  VAR OBESE_B100;
  SUBPOPX USEREC=1;
  SUBGROUP SURVEYC;
  LEVELS 9;
  TABLES SURVEYC;
  RTITLE "Obesity prevalence estimates NHANES 1988–94 to 2013–2014 –aged 2–19";
  OUTPUT NSUM MEAN SEMEAN ATLEV2 ATLEV1/ FILENAME=nh8814 FILETYPE=SAS REPLACE;
run;

```

SUDAAN code for Step 2. Assess nonlinearity: Fit logistic regression models using SUDAAN's PROC RLOGIST. The model includes both linear and quadratic time terms.

```

*Run logistic model with linear and quadratic time terms to assess nonlinearity;
PROC RLOGIST DATA=NHANES88_14 DESIGN=WR EST_NO=919000;
  NEST STRATUM PSU / MISSUNIT;
  WEIGHT WT2;
  SUBPOPX USEREC = 1;
  MODEL OBESE_B100 = TIMEPT TIMEPT_SQ;
  TEST SATADJF;
  OUTPUT BETA SEBETA P_BETA / BETAS=all BETAFMT=F6.4 SEBETAFMT=f7.4 FILENAME=betas
    FILETYPE=SAS REPLACE;
  OUTPUT /risk=default ORFMT=F6.3 LOWORFMT=F6.3 UPORFMT=F6.3 FILENAME=logor FILETYPE=SAS
    REPLACE;
  OUTPUT SATADJF SATADJP / SATADJFFMT=F4.2 SATADJPFMT=F6.4 FILENAME=satfn FILETYPE=SAS
    REPLACE;
  PRINT BETA="BETA" SEBETA="S.E." DEFT="Design Effect" T_BETA="T:BETA=0" P_BETA="P-VALUE"/
    TESTS=default t_BETAFMT=F8.2 DEFTFMT=F6.2 DFFMT=F7.0 WALDCHIFMT=F10.2
    WALDCHPFMT=F7.4;
  SETENV TOPMGN=0 COLSPCE=1 LABWIDTH=22 COLWIDTH=8 DECWIDTH=3;
  RTITLE "Logistic model obese_B100=TIMEPT TIMEPT_SQ";
run;

```

SAS code for Step 3. Transforms the obesity prevalence estimates and their standard errors to the log-odds scale for input into NCI's Joinpoint software.

```

*Input file from PROC DESCRIPT with obesity percentages and standard errors;
DATA OBESELN; SET nh8814;
*Transform the obesity prevalence estimates and their standard errors from percentages to proportions;
  P=MEAN/100;
  SEP=SEMEAN/100;

*Transform the proportions and their standard errors to the log-odds scale;
  LNP = LOG(P/(1-P));
  LNSEP = SEP/(P*(1-P));
run;

```

SAS and SUDAAN code for Step 4. Fit final trend model in SUDAAN's PROC RLOGIST, the logistic joinpoint regression model with a joinpoint at the midpoint of 2003–2004 cycle identified by NCI's Joinpoint software. [Table J](#)

Table J. Example B, values of variables used to parameterize the final joinpoint model fit using SUDAAN software to the trend in obesity prevalence among children and adolescents aged 2–19 years, by survey cycle: United States, 1988–1994 through 2013–2014

Survey cycle	TIMEPT	JOINPT	SEG1	SEG2
1988–1994	1.0	13.5	1.0	0
1999–2000	9.5	13.5	9.5	0
2001–2002	11.5	13.5	11.5	0
2003–2004	13.5	13.5	13.5	0
2005–2006	15.5	13.5	13.5	2
2007–2008	17.5	13.5	13.5	4
2009–2010	19.5	13.5	13.5	6
2011–2012	21.5	13.5	13.5	8
2013–2014	23.5	13.5	13.5	10

SOURCE: NCHS, National Health and Nutrition Examination Survey, 1988–1994 through 2013–2014.

shows the values of the variables used to parameterize the joinpoint regression model for the SUDAAN run.

*Create variables needed for joinpoint regression model;

```
DATA JPMODEL; SET NHANES88_14;
```

*Create variable to represent the location of the joinpoint;

```
JOINPT = 13.5; /*Joinpoint at 2003–2004 NHANES cycle*/
```

*Create variables to represent the 2 line segments for the logistic model with a joinpoint located at 2003–2004 NHANES cycle;

*1st line segment in the joinpoint model;

```
IF TIMEPT <= JOINPT THEN SEG1 = TIMEPT;
```

```
ELSE SEG1 = JOINPT; /*If TIMEPT>13.5*/
```

*2nd line segment in the joinpoint model;

```
IF TIMEPT <= JOINPT THEN SEG2 = 0;
```

```
ELSE SEG2 = TIMEPT - JOINPT;
```

```
run;
```

*Run logistic model with a joinpoint at 13.5 (2003–2004 NHANES cycle);

```
PROC RLOGIST DATA=JPMODEL DESIGN=WR EST_NO=919000;
```

```
NEST STRATUM PSU / MISSUNIT;
```

```
WEIGHT WT2;
```

```
SUBPOPX USEREC = 1;
```

```
MODEL OBESE_B100 = SEG1 SEG2;
```

```
CONTRAST 0 -1 1/NAME="Test for change in slope, SEG1 vs SEG2";
```

```
TEST SATADJF;
```

```
OUTPUT BETA SEBETA P_BETA/ BETAS=all BETAFMT=F6.4 SEBETAFMT=f7.4 FILENAME=betas
```

```
FILETYPE=SAS REPLACE;
```

```
OUTPUT / RISK=default ORFMT=F6.3 LOWORFMT=F6.3 UPORFMT=F6.3 FILENAME=logor FILETYPE=SAS
```

```
REPLACE;
```

```
OUTPUT SATADJF SAGTADJP / SATADJFFMT=F4.2 SATADJPFMT=F6.4 FILENAME=satfn FILETYPE=SAS
```

```
RFEPLACE;
```

```
PRINT BETA="BETA" SEBETA="S.E." DEFT="Design Effect" T_BETA="T:BETA=0" P_BETA="P-VALUE"/
```

```
TESTS=default T_BETAFMT=F8.2 DEFTFMT=F6.2 DFFMT=F7.0 WALDCHIFMT=F10.2
```

```
WALDCHPFMT=F7.4;
```

```
SETENV TOPMGN=0 COLSPCE=1 LABWIDTH=22 COLWIDTH=8 DECWIDTH=3;
```

```
RTITLE "Logistic model assessing change in trend at 2003–2004 in obesity prevalence, NHANES 1988–2014";
```

```
run;
```

Example C. Emergency Department Visits With an Electrocardiogram Ordered or Provided: NHAMCS, 2003–2012

This example uses record-level data on diagnostic and screening services ordered or provided at emergency department visits from the 2003–2012 NHAMCS. Change over the time period in the percentage of visits during which an electrocardiogram (EKG) was ordered or provided was of interest. Data are for patients of all ages.

Research question

How has the percentage of emergency department visits with an EKG ordered or provided changed during 2003–2012?

Time period of the analysis

The analysis includes the 10 years of NHAMCS data from 2003 through 2012. As advised in Guideline 1, the following rationale for the choice of the time period is provided. The analysis starts in 2003 because that is the year the two sample design variables, CSTRATM and CPSUM, were added to the NHAMCS public-use data files. These two variables were developed to replace two problematic masked design variables included on prior NHAMCS public-use files (40). The ending year of the study period is 2012 because it was the most recent year for which NHAMCS data were available at the time of the analysis. During these years, the data on EKG use during emergency department visits were collected using the same survey instrument (Guideline 1).

Observed time points included in the analysis

The observed time points included in the analysis are the 10 equally spaced data years, 2003–2012. Annual estimates computed for all ten NHAMCS surveys were used in the trend analysis, as advised in Guideline 2.a. No pooling across years occurred, as advised in Guideline 3.a. For the nonlinearity assessment and the regression analysis, the time variable (year) was scaled to the values 1–10 (i.e., 1 = 2003, ..., 10 = 2012) (Guideline 4.a.). Note that this scaling is possible because the time points are equally spaced.

Data source and type of data

The data are from an annual complex survey (NHAMCS) and are analyzed as record-level data (Guideline 5.a.). Users should combine both NHAMCS Outpatient Department Data (2003–2011) and Emergency Department Data (ED) (2003–2012) for accurate variance estimates.

Analysis approach

For ease of interpretation, a linear model was fit to the binary outcome variable (EKG ordered or provided at an emergency room visit) (Guideline 8.b.). All of the predicted values for the observed time points were found to be within the unit interval, which affirmed the appropriateness of using a

linear model (Guideline 8.b.). Because NHAMCS is a complex survey, record-level data were used with survey analysis software to obtain the annual estimates and their standard errors and to assess nonlinearity in the trend (Guidelines 5.a. and 7.b.). The trend was found to be linear. Therefore, the Joinpoint software was not needed. A linear trend model was fit using the record-level data and survey analysis software to obtain slope estimates and hypothesis tests (Guideline 5.a.). Specifics of the analysis are described in Steps 1 through 3 below.

Computer code

SAS and SUDAAN code for this example is provided following the “Conclusions” section.

Table K. Example C, observed percentage of emergency department visits during which an electrocardiogram was ordered or provided, by survey year: United States 2003–2012

Survey year	Time point value ¹	Percent	SE
2003	1	16.3	0.5
2004	2	16.6	0.5
2005	3	16.4	0.6
2006	4	17.1	0.5
2007	5	16.6	0.6
2008	6	18.2	0.5
2009	7	17.2	0.6
2010	8	18.6	0.7
2011	9	19.1	0.6
2012	10	17.9	0.8

¹These time values were used in all SUDAAN procedures to represent the survey years.

NOTES: Estimates of the percentages and their standard errors were obtained using record-level data and SUDAAN's PROC CROSSTAB. SE is standard error.

SOURCE: NCHS, National Hospital Ambulatory Medical Care Survey, 2003–2012.

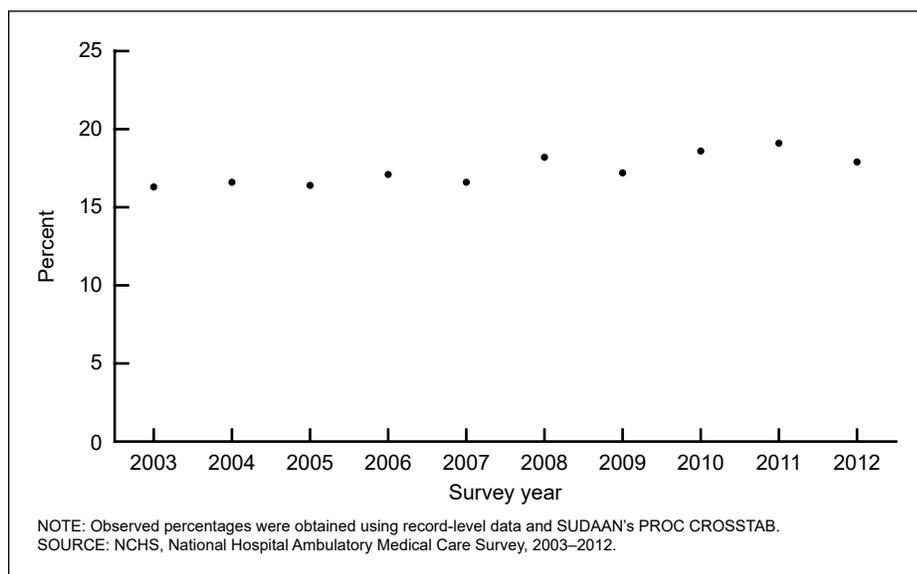


Figure 7. Example C, observed percentage of emergency department visits during which an electrocardiogram was ordered or provided, by survey year: United States, 2003–2012

Step 1. Compute annual survey estimates and plot the data

Estimates of the percentage of emergency department visits during which an EKG was ordered or provided and their standard errors were calculated in SUDAAN's PROC CROSSTAB using the appropriate sample weights and incorporating the complex sample

design (Guideline 5.a.) (15,16). The percentages and their standard errors can be seen in [Table K](#). [Figure 7](#) shows that there is fluctuation in the estimates over time, but indicates that the percentage of emergency department visits during which an EKG was ordered or provided generally has increased over time.

Step 2. Assessment of nonlinearity

The original time variable was scaled to the values 1–10 (i.e., 1 = 2003, ..., 10 = 2012) as shown in [Table K](#). To assess nonlinearity in the trend, SUDAAN's PROC REGRESS was used to fit a polynomial regression model with linear and quadratic time terms to the record-level data (Guideline 7.b.). The quadratic term was not statistically significant ($P = 0.862$), thus there was no evidence of nonlinearity in the trend.

Step 3. Obtaining final slope estimates and tests of trend

Because the quadratic term in the polynomial trend model was not statistically significant, the final trend model was a regression model with only a linear time term which was fit to the record-level NHAMCS data using SUDAAN's PROC REGRESS (Guideline 5.a.). The values 1–10 were used to represent the observed time points. As shown in [Table L](#) and [Figure 8](#), the regression model indicated that the percentage of emergency department visits during which an EKG was ordered or provided increased 0.27 percentage point each year during 2003–2012.

Conclusion

The percentage of emergency department visits during which an EKG was ordered or provided increased linearly during 2003–2012.

Table L. Example C, parameter estimates for the linear regression model fit using SUDAAN software to the trend in the percentage of emergency department visits during which an electrocardiogram was ordered or provided: United States, 2003–2012

Survey years	Slope	SE	P value of test that slope = 0
2003–2012	0.269	0.069	0.000

0.000 quantity more than zero but less than 0.0005.

NOTES: Estimates obtained using record-level data and SUDAAN's PROC REGRESS. SE is standard error.

SOURCE: NCHS, National Hospital Ambulatory Medical Care Survey, 2003–2012.

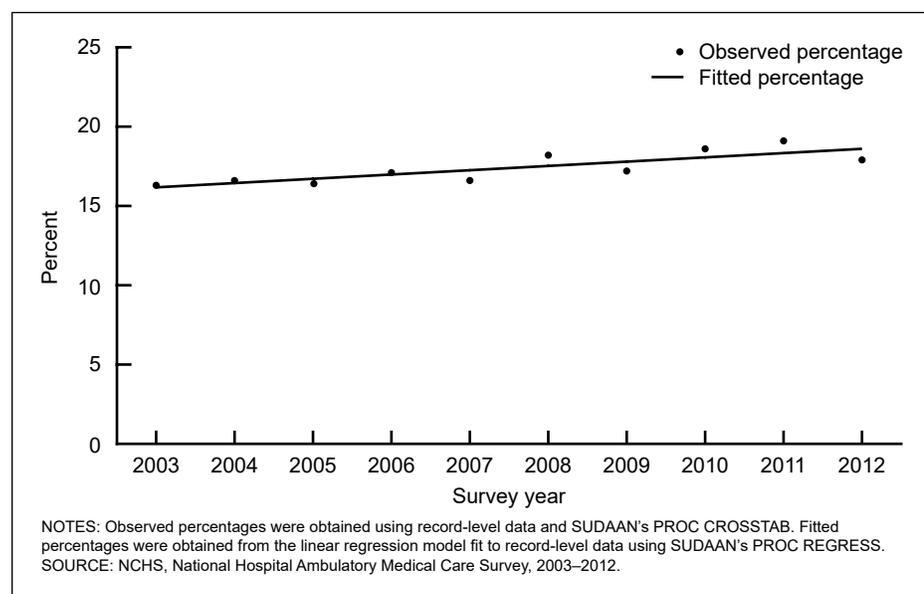


Figure 8. Example C, observed and fitted percentages of emergency department visits during which an electrocardiogram was ordered or provided, by survey year: United States, 2003–2012

SAS and SUDAAN code for Example C

SAS and SUDAAN code for Example C is provided below. The variables used in the SAS and SUDAAN code for Example C are shown in [Table M](#).

SUDAAN code for Step 1. Compute percentage of emergency department visits during which an electrocardiogram was ordered or provided during 2003–2012 using SUDAAN's PROC CROSSTAB.

```
PROC SORT DATA=NHAMCS03_12;
    BY CSTRATM CPSUM;
run;
```

Table M. Example C, variables used in the SAS and SUDAAN code for the National Hospital Ambulatory Medical Care Survey trend analysis of electrocardiograms ordered or provided at an emergency department visit, 2003–2012

Variable name	Variable description	Variable values
YEAR	Time variable, original, used in SUDAAN's PROC CROSSTAB	2003, ..., 2012
TIMEPT	Time variable, rescaled, used in SUDAAN's PROC REGRESS	1 = 2003 2 = 2004 ... 10 = 2012
TIMEPT_SQ	Quadratic time term used in SUDAAN's PROC REGRESS	TIMEPT*TIMEPT
CSTRATM	Clustered PSU stratum (masked)	Various
CPUSM	Clustered primary sampling unit (masked)	Various
SETTYPE	Variable indicating type of visit	1 = NAMCS 2 = Outpatient department visit 3 = Emergency department visit
NEWWT	Sample weight	PATWT/1000. PATWT is the original patient record weight.
EKG	EKG offered or provided during emergency department visit	1 = EKG offered or provided during emergency department visit 0 = EKG not offered or provided
EKG_B100	EKG offered or provided during emergency department visit, rescaled to percent, for use in SUDAAN's PROC REGRESS	100 = EKG offered or provided during emergency department visit 0 = EKG not offered or provided

NOTE: EKG is electrocardiogram.

SOURCE: NCHS, National Hospital Ambulatory Medical Care Survey, 2003–2012.

```

PROC CROSSTAB DATA=NHAMCS03_12 FILETYPE=SAS DESIGN=WR;
  NEST CSTRATM CPSUM /MISSUNIT;
  WEIGHT NEWWT;
  SUBPOPX SETTYPE = 3;
  CLASS YEAR EKG;
  TABLES YEAR*EKG;
  SETENV COLWIDTH = 10 DECWIDTH=3;
  PRINT/STYLE=nchs;
  PRINT NSUM WSUM SEWGT ROWPER SEROW/STYLE=nchs;

```

run;

SUDAAN code for Step 2. Assess nonlinearity by fitting a polynomial regression model using SUDAAN's PROC REGRESS. The model fit has both a linear time term and a quadratic time term.

*Polynomial regression model with linear and quadratic time terms. Time variable has been rescaled to have values of 1 to 10;

```

PROC SORT DATA = NHAMCS03_12;
  BY CSTRATM CPSUM;

```

run;

```

PROC REGRESS DATA=NHAMCS03_12 FILETYPE=SAS DESIGN=WR;
  NEST CSTRATM CPSUM /MISSUNIT;
  WEIGHT NEWWT;
  SUBPOPX SETTYPE = 3;
  MODEL EKG_B100 = TIMEPT TIMEPT_SQ;
  SETENV COLWIDTH = 10 DECWIDTH=4;
  PRINT BETA="BETA" SEBETA="S.E." T_BETA="T:BETA=0" P_BETA="P-VALUE"/ BETAfmt=F8.5
  SEBETAfmt=F8.5 P_BETAfmt=F8.5 STYLE=nchs;

```

run;

SUDAAN code for Step 3. Obtain final slope estimates and tests of hypotheses by fitting a linear regression model using SUDAAN's PROC REGRESS. The model has only a linear time term (no higher-order time terms or joinpoints).

*Model includes only the linear time term;

```
PROC REGRESS DATA=NHAMCS03_12 FILETYPE=SAS DESIGN=WR;
  NEST CSTRATM CPSUM /MISSUNIT;
  WEIGHT NEWWT;
  SUBPOPX SETTYPE = 3;
  MODEL EKG_B100 = TIMEPT;
  SETENV COLWIDTH = 10 DECWIDTH=4;
  PRINT BETA="BETA" SEBETA="S.E." T_BETA="T:BETA=0" P_BETA="P-VALUE"/ BETAfmt=F8.5
    SEBETAfmt=F8.5 P_BETAfmt=F8.5 STYLE=nchs;
```

run;

Example D. Teen Birth Rates, by Age Group: National Vital Statistics System, 1991–2015

This example uses aggregated teen birth data for 1991–2015 from the National Vital Statistics System. Birth rates for teenagers aged 15–17 and 18–19 were calculated based on the number of births to females in the specified age group divided by the estimated population of females in those groups (41,42). The birth rates are expressed as the number of births per 1,000 women. The formula used to compute the standard error of a birth rate is the same as that used to compute the standard error of a death rate and is presented in *Deaths: Final data for 2014* (43).

Research question

How has the birth rate for teenagers aged 15–17 and 18–19 changed during 1991–2015, and how do the trends differ between the age groups?

Time period of the analysis

As advised in Guideline 1, the following rationale for the choice of the time period to include in the analysis is provided. The time period of this analysis is 1991–2015. The starting year for the time period is 1991 because this is the year when the downward trend in teen birth rates is known to have begun (Guideline 1). The final year in the period is 2015 because it was the most recent year of data available at the time of analysis.

Observed time points included in the analysis

The observed time points are equally spaced and represent the 25 data years in the analysis, 1991–2015. As advised in Guideline 3.a., all of the 25 annual teen birth rates will be used in the trend analysis (i.e., no pooling across years will occur) and the trend will be assessed using all observed time points in the covered time period, as advised in Guideline 2.a. The values used to represent the observed time points (year) were not modified for this analysis.

Data source and type of data

Annual aggregated vital records data, based on 100% of the birth certificates registered in the United States from 1991 through 2015, were used (44).

Analysis approach

Because the data are vital records data, aggregated data have been used for the trend analyses (Guideline 6.a.). As described below, the annual birth rates and their standard errors were computed and input into NCI's Joinpoint software (Version 4.4.0.0) to assess nonlinearity, and obtain the joinpoint regression models, slope estimates, and tests of hypotheses (Guidelines 6.b., 7.b., 7.c., and 12.b.). The Joinpoint software's option to fit a log-linear model to the birth rates was used to obtain estimates of the annual percentage change in the rates (Guideline 6.c.). Specifics are described in Steps 1 through 2 below.

Step 1: Compute the annual estimates and plot the data

Annual teen birth rates and their standard errors were calculated using standard software and formulas as described above. Table N and Figure 9 show the birth rates during 1991–2015 for teenagers aged 15–17 and 18–19. The graph shows that for both age groups, the birth rate is considerably lower in 2015 than in 1991. The graph also indicates that changes in the trend may have occurred at several time points during the time period.

Step 2: Assess nonlinearity, estimate joinpoints for nonlinear trends, and fit the final trend models

Because the analysis involves aggregated vital records data, NCI's Joinpoint software was used to assess nonlinearity in the teen birth rate trends and to fit the final trend models (Guidelines 6.b., 7.b., 7.c., and 12.b.). The previously computed birth rates and their standard errors for each age group, (shown in Table N) and year of the estimate were input into the Joinpoint software with the specification that a natural log transformation of the rates be used in order to get estimates of the annual percentage change in the rates (Guideline 6.c.). The default settings for the minimum and maximum number of joinpoints to search for were used. The default settings for the minimum number

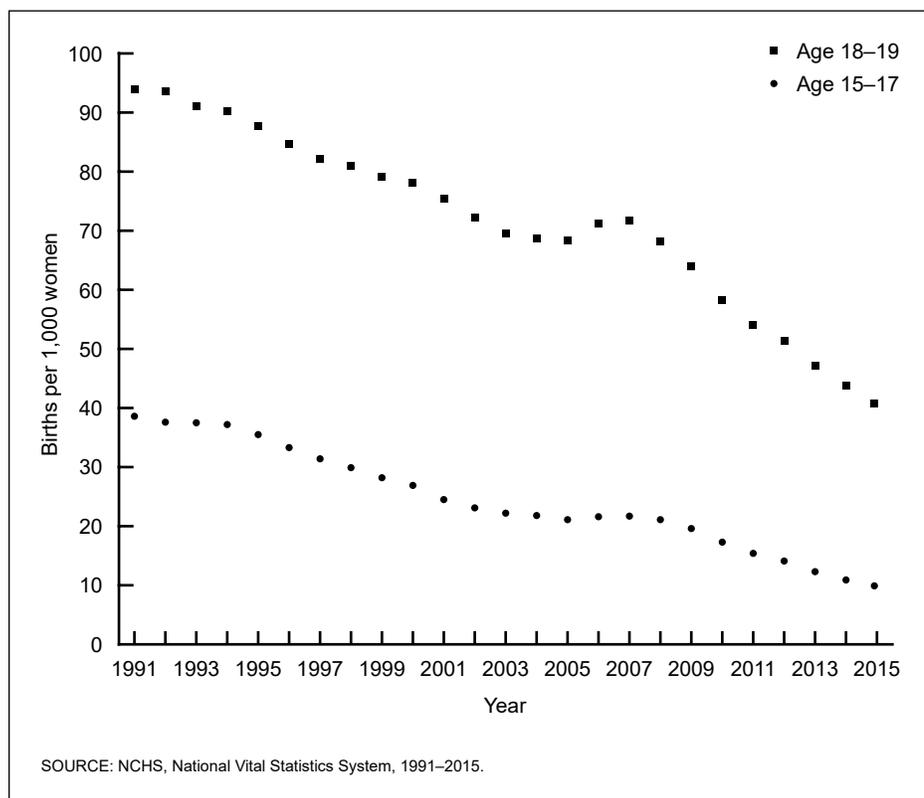
Table N. Example D, birth rates for teenagers aged 15–19, by age group and year: United States, 1991–2015

Year ¹	15–17 years		18–19 years	
	Rate	SE	Rate	SE
1991	38.6	0.089	94.0	0.163
1992	37.6	0.087	93.6	0.166
1993	37.5	0.086	91.1	0.163
1994	37.2	0.084	90.2	0.162
1995	35.5	0.081	87.7	0.158
1996	33.3	0.077	84.7	0.153
1997	31.4	0.074	82.1	0.149
1998	29.9	0.072	80.9	0.145
1999	28.2	0.070	79.1	0.142
2000	26.9	0.068	78.1	0.140
2001	24.5	0.064	75.5	0.138
2002	23.1	0.062	72.2	0.135
2003	22.2	0.061	69.6	0.131
2004	21.8	0.060	68.7	0.130
2005	21.1	0.058	68.4	0.129
2006	21.6	0.058	71.2	0.131
2007	21.7	0.058	71.7	0.130
2008	21.1	0.057	68.2	0.125
2009	19.6	0.056	64.0	0.120
2010	17.3	0.052	58.2	0.114
2011	15.4	0.050	54.1	0.112
2012	14.1	0.048	51.4	0.110
2013	12.3	0.045	47.1	0.106
2014	10.9	0.042	43.8	0.103
2015	9.9	0.040	40.7	0.099

These time values were used in NCI's Joinpoint software to represent the observed time points.

NOTES: Birth rate is births per 1,000 women. SE is standard error.

SOURCE: NCHS, National Vital Statistics System, 1991–2015.



SOURCE: NCHS, National Vital Statistics System, 1991–2015.

Figure 9. Example D, observed birth rates for teenagers aged 15–19, by age group and year: United States, 1991–2015.

of observed time points in the beginning, middle, and ending line segments of a joinpoint regression model (Guideline 12.f.) were used as was the requirement that all joinpoints fall on observed time points (Guidelines 11.a. and 12.e). The Joinpoint software fit weighted least-squares joinpoint regression models based on the identified joinpoints (Guideline 6.b.), and estimated and tested the slopes of the line segments (Guidelines 6.b., 7.c., and 12.b.).

The following settings were used for the Joinpoint (Version 4.4.0.0) software runs:

- type of estimate = crude rate,
- natural log transformation of the birth rates (Guideline 6.c.),
- weighted least-squares,
- Grid search method for detecting joinpoints, with no joinpoints allowed to fall between adjacent observed time points (Guidelines 11.a. and 12.e.),
- uncorrelated errors model (Guideline 12.h.),
- minimum and maximum number of joinpoints to search for set at the Joinpoint software defaults for 25 observed time points: minimum number of joinpoints = 0, maximum number = 4, (Guideline 12.f.),
- minimum number of observed time points in the beginning and ending line segments (including the beginning or ending joinpoint) set at the Joinpoint software (Version 4.4.0.0) default = 3 (Guideline 12.f.),
- minimum number of observed time points in a middle line segment (including the joinpoints on each end of the line segment) set at the Joinpoint software (Version 4.4.0.0) default = 4 (Guideline 12.f.), and
- permutation test as the model selection method (Guideline 12.g.), with an overall alpha level equal to 0.05 and the number of randomly permuted data sets set to the default ($n = 4,999$).

As shown in Table O and in Figure 10, the Joinpoint program found three joinpoints in the birth rate trend observed for teenagers aged 15–17 (1994, 2003, and 2008) and three in the trend for

teenagers aged 18–19 (2000, 2004, and 2007). Estimates of the annual percentage rate change for each line segment were obtained by transforming the slopes (100*(exp(β)-1)).

Table O. Example D, parameter estimates and estimated annual percent change for joinpoint regression models fit using the National Cancer Institute's Joinpoint software to birth rate trends for teenagers aged 15–17 and 18–19: United States, 1991–2015

Age group and joinpoint regression model line segments	Slope	SE	APC ¹	P value of test that slope = 0	P value of test that slopes do not differ
15–17 years (3 joinpoints: 1994, 2003, 2008)					
1991–1994	-0.007	0.007	-0.6	0.395	2v1: 0.000
1994–2003	-0.059	0.002	-5.8	0.000	3v2: 0.000
2003–2008	-0.005	0.006	-0.5	0.342	4v3: 0.000
2008–2015	-0.110	0.003	-10.4	0.000	4v1: 0.000 4v2: 0.000
18–19 years (3 joinpoints: 2000, 2004, 2007)					
1991–2000	-0.023	0.001	-2.2	0.000	2v1: 0.096
2000–2004	-0.034	0.006	-3.3	0.000	3v2: 0.001
2004–2007	0.023	0.013	2.4	0.085	4v3: 0.000
2007–2015	-0.072	0.002	-6.9	0.000	4v1: 0.000 4v2: 0.000

0.000 Quantity more than zero but less than 0.0005.
¹Computed as 100*(exp(β)-1).

NOTES: NCI's Joinpoint software (Version 4.4.0.0) was used to fit weighted least-squares regression models to the birth rates on the log scale with the standard errors of the birth rates used as the weights. For the Joinpoint software run, a minimum of three observed time points in the beginning and ending line segments (including the joinpoint) and a minimum of four observed timepoints in any middle line segment (including the two joinpoints) were allowed. A minimum of zero and a maximum of four joinpoints were searched for using the Grid search algorithm, the permutation test, and an overall alpha level of 0.05. SE is standard error. APC is annual percent change. NCI is National Cancer Institute.

SOURCE: NCHS, National Vital Statistics System, 1991–2015.

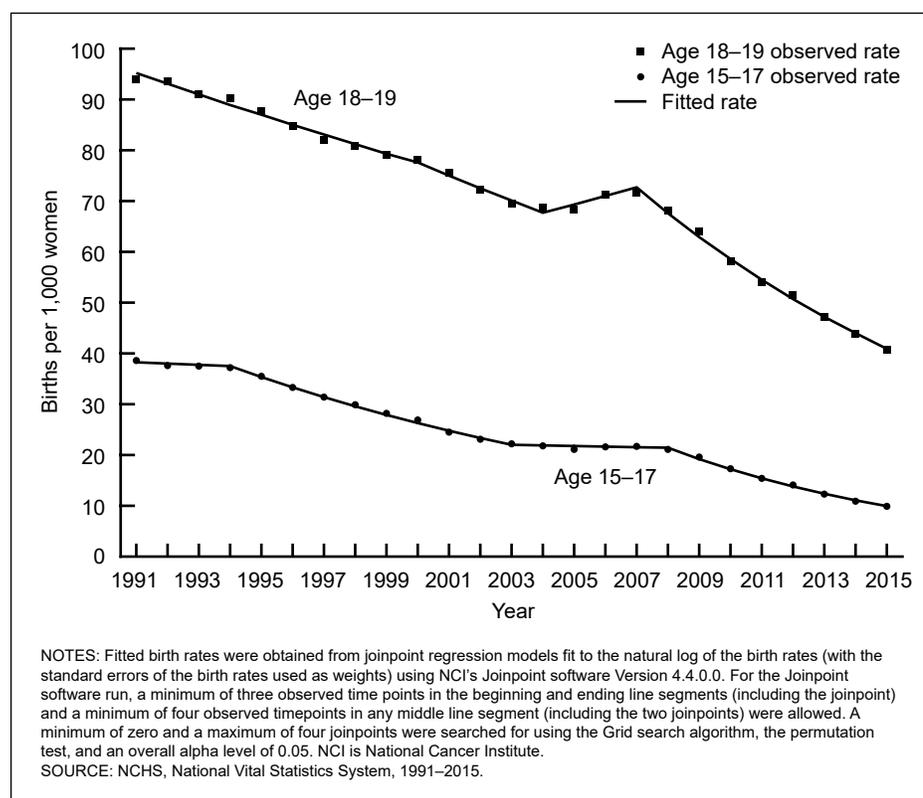


Figure 10. Example D, observed and fitted birth rates for teenagers aged 15–19, by age group and year: United States, 1991–2015

For the younger teenagers, birth rates were stable during 1991–1994, declined at a rate of almost 6% per year during 1994–2003, were stable during 2003–2008, and declined at a rate of about 10% per year during 2008–2015. Note that as specified in Guidelines 11.a. and 12.d., the line segments of the trend are described as 1991–1994, 1994–2003, 2003–2008, and 2008–2015. It would not be correct to label the second and later line segments as 1995–2003, 2004–2008, 2009–2015 because this would imply that the line segments do not connect at the joinpoints and that the changes between 1994–1995, 2003–2004, and 2008–2009 were not taken into account in the analysis.

For the older teenagers, birth rates declined during 1991–2000 and 2000–2004, were stable during 2004–2007, and declined during 2007–2015. The rate of decline during the second period was not statistically significantly faster than that during the first period; the rate of decline during the last period was faster than during the first and second periods.

Conclusions

In general, the birth rate trends for teenagers aged 15–17 and 18–19 during 1991–2015 were similar. Both groups showed overall declines, with the fastest declines occurring in the latter part of the time period, though the slopes differed for some of the trend segments. The location of the joinpoints differed slightly for the two groups, but were within the confidence interval for the corresponding joinpoint of the other group; suggesting (without applying a formal significance test) that the two joinpoints could share a similar location.

Among teenagers aged 15–17, birth rates were stable during 1991–1994, declined at an average annual rate of about 6% per year during 1994–2003, were stable during 2003–2008, and then declined at an average annual rate of about 10% per year during 2008–2015.

Among those aged 18–19, birth rates declined at an average annual rate of about 2% per year during 1991–2000, about 3% per year during 2000–2004, and about 7% per year during

2007–2015. The birth rates for this age group were stable during 2004–2007.

For both teen age groups, three joinpoints were identified in the birth rate trend during 1991–2015, though the locations of the joinpoints were not the same. For both age groups, rates of decline in the birth rates during the second and fourth time periods were statistically significant, with the rate of decline faster in the final period than in the second.

Future Research

This report has identified a number of areas where methodological work could facilitate trend analyses of NCHS data. These include:

Selection of start time

Develop a data-based procedure to select the start time for a trend analysis when there is no obvious choice based on availability, data comparability, external event, prior research, or other such reason. Given that a trend analysis that covers a specific range of years is needed and that there are earlier (or later) years available that could be included, a method is needed (possibly based on similar principles as joinpoint) that selects both a trend line and starting and ending points that are relatively stable within the original target interval. Some argue that as many years of data as are available should be included in a trend analysis because a longer series can better characterize the trend, but this remains an open question and warrants further study.

More specific guidance on collapsing years in a trend analysis

The current guidance to leave data unpooled for a trend analysis is based on results from a simple random sample with known variance. It would be useful to determine whether this advice should be modified with regards to NCHS complex surveys and to quantify the impact of pooling.

Incorporate survey design-based estimation and testing in NCI's Joinpoint software

Add features to NCI's Joinpoint software so that it can appropriately adjust for any year-to-year correlation due to the survey design and employ appropriate degrees of freedom for hypothesis tests.

Develop additional joinpoint model selection criteria or procedures

Develop a criterion or procedure that results in a model with significant differences between the slopes for all adjacent line segments, according to a statistical test.

Develop guidance for choosing among the model selection methods

Conduct simulations to develop guidance regarding when to use the permutation test, the BIC test, the modified BIC test, or the BIC3 test (number of time points in the analysis, presence of year-to-year correlation, use of predicted means, etc.).

Pursue estimation and model fitting in a framework where all relevant models are special cases of one general model

For example, the use of polynomial spline models when both joinpoint models and polynomial models are of interest.

Develop nonparametric tests of trend for surveys

The CMHT closely resembles a parametric test of a regression on ordinal data as if they were interval. More general tests are needed; an example is a test to determine whether a trend is based on a steady increase or decrease through time, without regard to an exact form.

Develop a goodness-of-fit test

This could be useful in assessing how much confidence to have in the model. When an outcome is rare, the estimates for the time points can be unstable, and sometimes the selected joinpoint model does not appear to fit all that well. A goodness-of-fit test could indicate whether or not the model fit is acceptable. Additionally, a goodness-of-fit test could be useful when trying to determine a common joinpoint model for a set of subgroups.

Summary

This report discusses issues that should be considered when conducting a trend analysis using NCHS data and presents analysis guidelines related to each issue discussed. Some of the issues considered apply to all trend analyses, such as selection of the time points to include in the analysis; others relate to the type of data (survey data or vital records data, record-level or aggregated), to whether the trend is linear or nonlinear, and to assorted other topics. As for any statistical analysis involving modeling, analytic choices must be made during the course of a trend analysis that will impact the results. The report discusses the strengths and limitations of different choices.

Particular attention is paid to joinpoint regression modeling of trends and the use of NCI's Joinpoint software to do so because the primary use of trend analysis at NCHS is to describe trends in health measures over time and to identify changes (magnitude or direction) in those trends. The NCI Joinpoint software is, currently, the preferred software for identifying joinpoints in trends in NCHS vital records and survey data, despite the issues for its use with survey data. This is because it is the most user-friendly standalone software that identifies the number and location of joinpoints and produces slope estimates and hypothesis tests. While this report focuses on time trend analyses, the issues discussed and guidelines presented are applicable to trend analyses involving other ordinal or interval variables, such as age or income. The twelve issues discussed in this report and their associated guidelines are listed below.

Guideline for Issue 1: Choosing the time period to include in a trend analysis and providing the rationale

Provide a rationale for the choice of the time period included in the trend analysis. If there are concerns about the choice of the time period, discuss them, when appropriate, as a limitation of the analysis.

Guidelines for Issue 2: Using all time points or just the beginning and ending time points to assess a trend

- In most situations, assess a trend and measure change using all time points rather than computing change using only the beginning and ending time points.
- If a trend analysis that uses all of the time points shows that the trend is linear, then for some types of reports, it may be desirable to report change between the beginning and ending time points.
- Measuring change between two time points may be necessary for reports that present large numbers of health measures such as *Healthy People and Health, United States*.

Guidelines for Issue 3: Pooling data across years or cycles

- When assessing a trend by fitting a model, it generally is not desirable to pool data across the observed time points.
- Regardless of how a trend was estimated, if data for the time points used in the trend analysis cannot be displayed due to reliability or confidentiality guidelines or if the data values for the time points are unstable, pooled estimates could be displayed (provided the trend produced using pooled estimates does not differ substantively from that produced using unpooled estimates).

Guidelines for Issue 4: Choosing values to represent the observed time points

- When the observed time points in a trend analysis are equally spaced, any set of values can be used to represent them in a trend model.
- When the observed time points in a trend analysis are unequally spaced or are intervals of unequal length, the values used to represent them in a trend model should reflect this.

Guidelines for Issue 5: Considerations for trend analyses of survey data

- When analyzing survey data, generally use record-level data and survey analysis software to fit the desired trend model so as to incorporate the survey design and sample weights, adjust for year-to-year correlation, and properly compute degrees of freedom.
- A partial exception to using record-level survey data is made when changes in the trend will be assessed using joinpoint regression models fit with NCI's Joinpoint software. NCI's Joinpoint software may be used with aggregated data to identify the number and location of joinpoints. Survey analysis software is then used with record-level data to obtain final slope estimates and tests of hypothesis for the model identified by the Joinpoint software ([Issue 12](#)).
- Aggregated survey data may be used for trend analyses in large data reports, when record-level analysis is either not possible or not feasible. However, the report should make note of this.

Guidelines for Issue 6: Considerations for trend analyses of vital records data

- It is acceptable to use aggregated data for trend analyses of vital records data.
- NCI's Joinpoint software can be used to fit a straight line or a joinpoint regression model (estimate the observed time points at which changes in trend occur, estimate the slopes of the line segments and their variance, and conduct hypothesis tests) to aggregated vital records data. Typically, the software's weighted least-squares option is used.
- Log-linear models facilitate comparison of trends for groups or outcomes with large differences in observed data values. When a log-linear model is used, the estimated annual percentage

rate change is computed as $100 * (\exp(\beta) - 1)$.

Guidelines for Issue 7: General approach for conducting trend analyses

- When there are only three observed time points, a test for trend can be performed to determine whether the trend is nonlinear or linear (and if linear, whether it is increasing, decreasing, or stable). A justification should be provided if instead of fitting a trend model, the pairwise differences among the three observed time points are quantified and tested (the tests' significance level should be adjusted for multiple comparisons).
- To assess a trend for nonlinearity, consider using polynomial regression, orthogonal polynomial contrasts, joinpoint regression, or restricted cubic spline regression (if there are sufficient observed time points).
- If a trend is nonlinear and a goal of the analysis is to model the nonlinearity to improve the fit of the model, consider fitting a regression model with polynomial time terms. If a trend is nonlinear and a goal of the analysis is to identify where changes in the trend occur and to quantify them, consider fitting a joinpoint regression model.

Guidelines for Issue 8: Trend analyses with binary outcome variables

- When the outcome variable is binary, a logistic model often is fit to the trend. If NCI's Joinpoint software will be used to identify joinpoints and a logistic model will be used to obtain final estimates of the trend, transform the proportions and their standard errors to the log-odds scale before inputting them into Joinpoint.
- Using a linear model rather than a logistic model when conducting a trend analysis on a binary outcome variable may be preferable because it provides more interpretable slope

estimates. A linear model can be fit to binary data (coded as “0” and “1” or as “0” and “100”) if the estimated trend line is within the unit interval for the time points under study.

Guidelines for Issue 9: Trend analyses with covariates

- a. If the trend is linear, covariates can be included in trend analyses using standard modeling approaches.
- b. If the trend is nonlinear and will possibly include joinpoints, it is preferable to incorporate the covariates in the analysis when determining the number and location of any joinpoints.

Guideline for Issue 10: Cochran-Mantel-Haenszel test of trend

When outcomes are ordinal or nominal with three or more categories the CMH test for trend may be useful. When an outcome is binary, a CMH test of linear time trend using SUDAAN will be similar to the results from a linear regression model.

Guidelines for Issue 11: Locating joinpoints at or between observed time points

- a. Generally specify that joinpoints be located at observed time points, not between them.
- b. If joinpoints are located between observed time points, interpreting a joinpoint as the actual time when a trend changes is an incorrect interpretation.

Guidelines for Issue 12: Trend analyses of NCHS data using NCI’s Joinpoint Trend Analysis software

- a. If the data are record-level survey data NCI’s Joinpoint software may be used to estimate the joinpoints for a nonlinear trend, and then survey analysis software used to fit and test the indicated joinpoint model. If the slopes of two adjacent line segments in the fitted joinpoint regression model are not statistically

significantly different (based on the hypothesis tests obtained from the survey analysis software), consider dropping the joinpoint between them and refit the reduced model (using the survey analysis software). Provide a rationale.

- b. If the data are vital records data or aggregated survey data, NCI’s Joinpoint software can be used to obtain slope estimates and tests of the hypothesis for a linear or joinpoint model. Even if the slopes of two adjacent line segments in the model selected by the Joinpoint software are not statistically significantly different, generally report the model with all identified joinpoints and describe the two segments separately without regard to the *t*-test of the difference between the slopes.
- c. If a goal of the trend analysis is to assess whether the final observed time point represents a change in the trend, joinpoint regression can be used to make this assessment. One approach is to extend a previously identified joinpoint regression model to include the last observed time point and specify a new joinpoint at the next-to-last observed time point. Another approach is to use NCI’s Joinpoint software to fit a new joinpoint regression model to the extended time period (with the default spacing between joinpoints overridden so that a joinpoint can occur at the next-to-last observed time point). For record-level data, any such model identified using NCI’s Joinpoint software would subsequently be fit and tested using survey analysis software.
- d. When describing the trend associated with a joinpoint regression model and specifying the line segments, refer to the beginning line segment as extending from the first observed time point through the first joinpoint, the first middle line segment as extending from the first joinpoint through the second joinpoint (and so on), and the ending line segment as extending from the last joinpoint to the last observed time point.

For some trends, it may be more appropriate to provide a more general description of the trend and to present the confidence limits of the joinpoint locations.

- e. Generally, use the Grid method to search for joinpoints and specify that no joinpoints be located between observed time points.
- f. Review carefully the analytic considerations before choosing the settings for the minimum and maximum number of joinpoints to search for and the settings for the minimum number of observed time points in the beginning and ending line segments or the middle line segments. The default settings are not always the most appropriate choice. For example, the default settings may not be appropriate if a significant polynomial term was identified in the nonlinearity assessment. In this case, consider overriding the software default setting for the maximum number of joinpoints to search for to reflect this and consider specifying minimum line segment lengths less than the defaults to allow flexibility in joinpoint location. If there is interest in determining if a joinpoint is located at the next to last observed time point or, if there is interest in assessing volatility in the middle of the time period, then the minimum number of observed time points in the beginning, ending, and middle line segments should be set to allow maximum flexibility.
- g. For trend analyses with 10 or more time points, consider using the permutation test for model selection. If there are fewer than 10 time points but the samples are large or predictive margins are the input data, consider using the BIC criterion for model selection. Analytic considerations may indicate a different test choice.
- h. Do not fit joinpoint regression models using the auto-correlation options of the Joinpoint software.
- i. When logistic regression is used to model a trend in a binary outcome variable, transform the proportions

(or predictive margins) and their standard errors to the log-odds scale prior to inputting them into the Joinpoint software. Then specify a linear model for the Joinpoint program run. If covariates will be included in the final joinpoint model, consider using predictive margins and their standard errors as input to NCI's Joinpoint software. If age-adjusted rates computed using standard population counts applied to record-level survey data are the input data for NCI's Joinpoint software, fit the final joinpoint model using sample weights adjusted for the standard population counts.

- j. When describing the joinpoint analysis, list the maximum number of joinpoints searched for, the minimum number of observed time points allowed in the beginning, ending, and middle line segments (if only one joinpoint is searched for, specification of the minimum number of time points in the middle line segment is unnecessary), the type of dependent variable analyzed, the heteroscedastic error option and the search and model selection methods used and the overall alpha level, whether a log transformation was applied, any auto-correlation that was used, and any special features used. See above for suggested wording.

This is a working document. As trend analysis techniques and software capabilities develop and change, the guidelines may be revised.

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Appendix I. Three Methods for Estimating Slope in Trend Analyses of Survey Data

The three methods for estimating slope in trend analyses of survey data described below generally produce similar, but not identical, estimates. This appendix explains how the three methods differ, and thus why they do not always produce identical estimates of slope.

Method 1—Uses record-level data. As described on pages 92–93 of Korn and Graubard (20), it regresses individual outcomes on time and is implemented in survey analysis software regression procedures such as SUDAAN’s PROC REGRESS (see SUDAAN 11 Language Manual, page 282) (16).

Method 2—Uses aggregated data. Regresses the average aggregated outcomes on time and is implemented in complex survey software procedures such as SUDAAN’s PROC DESCRIPT with a “POLY” statement that includes a linear term. An example of this usage can be found on page 413 of Volume I of the SUDAAN 11 Language Manual (16).

Method 3—Uses aggregated data. Regresses the average aggregated outcomes on time with outcomes weighted by the inverse of their estimated sampling variance (a weighted least-squares version of Method 2) (45).

Briefly, the three estimation methods differ in how the sample weights are used. The first method can be thought of as performing a regression analysis that gives each individual in the population equal weight. However, since only a sample is available, the sampling weights are used to provide an estimate for the entire population. The second method can be thought of as performing a regression analysis using the population averaged at each time point. In the second method, sampling weights are used to estimate each population average. The third approach takes the second approach one step further. Instead of regressing on only the estimates of population average, each average is further weighted inversely by its estimated sampling variability. This latter approach mimics the weighted least-squares approach used in standard regression analysis where a specific, finite, population is not being considered.

The estimates that result from using Methods 1 or 2 are typically obtained by using record-level data together with sample design information input into survey analysis software. Estimates that result from using Method 3 are calculated using aggregate estimates along with their sample variances.

For simplicity, the comparison of the estimates from the three methods is only made for the case of a linear trend and a binary outcome variable. Slope estimates obtained for the three methods for other types of trends, such as quadratic trends and splines, exhibit similar differences, as long as they fit into the least-squares regression framework.

Notation

Years are indexed by $t = 1, 2, 3, \dots, T$,

$y_{it} = 0$ or 1 to indicate the absence/presence of an outcome for unit i sampled at time t ,

w_{it} = the sample weight for unit i , sampled at time t ,

N_t = population total at time t ,

$\hat{N}_t = \sum_i w_{it}$ the estimate of the population total, N_t , at time t ,

$\hat{t} = \sum_{t=1}^T t \hat{N}_t / \sum_{t=1}^T \hat{N}_t$ is the estimated average year over the population (i.e., $\sum_{t=1}^T t N_t / \sum_{t=1}^T N_t$),

$\bar{T} = \sum_{t=1}^T t / T$,

$\hat{Y}_t = \frac{\sum_i w_{it} y_{it}}{\hat{N}_t}$, is the estimate of population prevalence, \bar{Y}_t , at time t ,

\hat{V}_t is the estimated variance of \bar{Y}_t .

Method 1

For Method 1, the slope estimate takes the form:

$$\hat{B}_1 = \frac{\sum_{t=1}^T \hat{N}_t \hat{Y}_t (t - \hat{t})}{\sum_{t=1}^T \hat{N}_t (t - \hat{t})^2} \quad (1)$$

From the finite population perspective, Method 1 provides the following estimate of slope when the entire population is measured:

$$B_1 = \frac{\sum_{t=1}^T N_t \bar{Y}_t (t - \bar{t})}{\sum_{t=1}^T N_t (t - \bar{t})^2}$$

where, \hat{B}_1 is the estimate of B_1 , the population estimate of slope recommended by Korn and Graubard on page 93 (20) and Heeringa, *et al.* (21).

Method 2

For Method 2, the slope estimate takes the following form:

$$\hat{B}_2 = \frac{\sum_{t=1}^T \hat{Y}_t (t - \bar{T})}{\sum_{t=1}^T (t - \bar{T})^2} \quad (2)$$

From the finite population point of view, Method 2 estimates the slope based on the entire population as:

$$B_2 = \frac{\sum_{t=1}^T \bar{Y}_t (t - \bar{T})}{\sum_{t=1}^T (t - \bar{T})^2}$$

Note that if the estimate of the population, N_t , does not change from year to year, then $\hat{B}_1 = \hat{B}_2$.

Method 3

For Method 3, the slope estimate takes the following form:

$$\hat{B}_3 = \frac{\sum_{t=1}^T \hat{V}_t^{-1} \hat{Y}_t (t - \bar{T})}{\sum_{t=1}^T \hat{V}_t^{-1} (t - \bar{T})^2}, \quad (3)$$

From the finite population point of view, Method 3 estimates:

$$B_3 = \frac{\sum_{t=1}^T V_t^{-1} \bar{Y}_t (t - \bar{T})}{\sum_{t=1}^T V_t^{-1} (t - \bar{T})^2}$$

where, V_t is the variance of \hat{Y}_t .

The equation for B_3 shows that the Method 3 estimator, \hat{B}_3 , may have a questionable interpretation because it changes if the sampling variance changes. In other words, it is sensitive to sample design changes. However, Method 3 may not produce estimates that differ much from the other approaches, provided that the sampling variance is constant over time or if it is inversely proportional to the population size.

Appendix II. The Effect of Pooling Data Over Time on the Variance of a Slope Estimate

In this Appendix, the estimated variance of the slope obtained when a trend line is fit to the estimates from n time points is compared to that obtained when a line is fit to pooled estimates.

Suppose the estimates for the n time points are independent and their variances are equal and known.

Pool the estimates into k groups of $m = n/k$ estimates each. For example, if there are $n = 10$ annual estimates, they could be formed into $k = 5$ groups of $m = 2$ years each.

Notation

Let, y_{ij} be the estimate for observed time point j (e.g., year or cycle) of group i . For example, if three observed time points are pooled in each group, then y_{11} is the estimate for the first observed time point in group 1, y_{12} is the estimate for the second observed time point, and y_{13} is the estimate for the third observed time point.

$\bar{y}_i = \frac{\sum_{j=1}^m y_{ij}}{m}$ be the pooled estimate for group i , the average of the m estimates in the group,

x_{ij} denote which of the n time points is associated with the j th time point in the i th group (e.g., $x_{22} = 4$),

$\bar{x}_i = \frac{\sum_{j=1}^m x_{ij}}{m}$, denote the midpoint of the m time points in the i th group (e.g., $\bar{x}_1 = 1.5$),

$\bar{x} = \frac{\sum_i \sum_j x_{ij}}{mk}$. Denote the midpoint of the n time points.

Define $V(y_{ij}) = \sigma^2$, the variance of the ij th estimate.

Then, the variance of the pooled estimate is $V(\bar{y}_i) = \sigma^2/m$, (a smaller variance than that of the individual estimates).

Unpooled data

The slope estimate for a line obtained by fitting a linear regression model to the estimates for the n time points is:

$$\hat{b} = \frac{\sum_i \sum_j y_{ij} (x_{ij} - \bar{x})}{\sum_i \sum_j (x_{ij} - \bar{x})^2}$$

and the estimate of the variance of the slope \hat{b} is:

$$V(\hat{b}) = \frac{\sigma^2}{\sum_i \sum_j (x_{ij} - \bar{x})^2}.$$

Pooled data

The slope estimate for a line obtained by fitting a linear regression model to the k pooled time points is:

$$\hat{b}_g = \frac{\sum_i \bar{y}_i (\bar{x}_i - \bar{x})}{\sum_i (\bar{x}_i - \bar{x})^2},$$

and the estimate of the variance of the slope is:

$$V(\hat{b}_g) = \frac{\sigma^2}{\sum_i m (\bar{x}_i - \bar{x})^2}.$$

Because, $\sum_i \sum_j (x_{ij} - \bar{x})^2 = \sum_i \sum_j (x_{ij} - \bar{x}_i)^2 + \sum_i m (\bar{x}_i - \bar{x})^2$,

it follows that

$$\sum_i \sum_j (x_{ij} - \bar{x})^2 \geq \sum_i m (\bar{x}_i - \bar{x})^2$$

and therefore,

$$V(\hat{b}_g) = \frac{\sigma^2}{\sum_i m (\bar{x}_i - \bar{x})^2} \geq \frac{\sigma^2}{\sum_i \sum_j (x_{ij} - \bar{x})^2} = V(\hat{b}).$$

Thus, pooling results in a larger estimated variance for the slope estimate, which could result in failure to detect a significant trend. Hence, when conducting a trend analysis, it is better to use the original observations and not pool them.

Appendix III. Assessing Nonlinear Trends With Three Time Points

This section compares three methods for assessing nonlinear trends when there are three time points. The three methods are pairwise comparisons, orthogonal polynomial regression, and orthogonal polynomial contrasts. It is assumed that the variances and covariances of the point estimates are known. The general results also apply to the case when the variances and covariances are unknown and must be estimated from the sample; though in this case t scores are used instead of z scores.

Notation

Years are indexed by $t = 1, 2, 3$,

y_{it} = the 0/1 indicator of absence/presence of an outcome for unit i sampled at time t ,

w_{it} = the sample weight for unit i , sampled at time t ,

N_t = the population at time t ,

$\hat{N}_t = \sum_i w_{it}$ is the estimate of the population total, N_t , at time t ,

\bar{Y}_t = the population prevalence at time t ,

$\hat{\bar{Y}}_t = \frac{\sum_i w_{it} y_{it}}{\hat{N}_t}$ is the estimated population prevalence at time t .

When the sample is large and the variances and covariances are known, it can be assumed that the prevalence estimates are normally distributed as:

$$\begin{bmatrix} \hat{\bar{Y}}_1 \\ \hat{\bar{Y}}_2 \\ \hat{\bar{Y}}_3 \end{bmatrix} \sim N \left(\begin{bmatrix} \bar{Y}_1 \\ \bar{Y}_2 \\ \bar{Y}_3 \end{bmatrix}, \begin{bmatrix} v_1^2 & v_{12} & v_{13} \\ v_{12} & v_2^2 & v_{23} \\ v_{13} & v_{23} & v_3^2 \end{bmatrix} \right).$$

Pairwise comparisons of estimates

When pairwise differences among three estimates are to be made, the following three hypotheses must be tested:

$$H_1: \bar{Y}_1 - \bar{Y}_2 = 0 \text{ vs } \bar{Y}_1 - \bar{Y}_2 \neq 0$$

$$H_2: \bar{Y}_2 - \bar{Y}_3 = 0 \text{ vs } \bar{Y}_2 - \bar{Y}_3 \neq 0$$

$$H_3: \bar{Y}_1 - \bar{Y}_3 = 0 \text{ vs } \bar{Y}_1 - \bar{Y}_3 \neq 0$$

These three hypotheses are equivalent to:

$$H_1: D_1 = 0 \text{ vs } D_1 \neq 0$$

$$H_2: D_2 = 0 \text{ vs } D_2 \neq 0$$

$$H_3: D_1 + D_2 = 0 \text{ vs } D_1 + D_2 \neq 0,$$

where $D_1 = \bar{Y}_1 - \bar{Y}_2$ and $D_2 = \bar{Y}_2 - \bar{Y}_3$.

Define the estimated differences as $d_1 = \hat{\bar{Y}}_1 - \hat{\bar{Y}}_2$ and $d_2 = \hat{\bar{Y}}_2 - \hat{\bar{Y}}_3$. The differences are normally distributed as:

$$\begin{bmatrix} d_1 \\ d_2 \end{bmatrix} \sim N \left(\begin{bmatrix} D_1 \\ D_2 \end{bmatrix}, \begin{bmatrix} \sigma_1^2 & \sigma_{12} \\ \sigma_{12} & \sigma_2^2 \end{bmatrix} \right),$$

where $\sigma_1^2 = v_1^2 + v_2^2 - 2v_{12}$, $\sigma_2^2 = v_2^2 + v_3^2 - 2v_{23}$, and $\sigma_{12} = v_{12} + v_{23} - v_2^2 - v_{13}$.

The three individual two-sided hypothesis tests (unadjusted for multiple testing) are:

$$\text{Reject } H_1 \text{ if } |d_1| > z_{\frac{\alpha}{2}} \sigma_1,$$

$$\text{Reject } H_2 \text{ if } |d_2| > z_{\frac{\alpha}{2}} \sigma_2 \text{ and}$$

$$\text{Reject } H_3 \text{ if } |d_1 + d_2| > z_{\frac{\alpha}{2}} \sqrt{\sigma_1^2 + \sigma_2^2 + 2\sigma_{12}}.$$

Using the Bonferroni procedure to adjust the significance level for performing three pairwise tests requires using $\alpha/6$ instead of the $\alpha/2$ used above in the unadjusted tests. This adjustment makes rejection of the null hypothesis more difficult.

Orthogonal polynomial regression

Polynomial regression based on the method used in SUDAAN's PROC REGRESS is illustrated here. The regression model that corresponds to fitting an orthogonal quadratic polynomial to the estimates for three time points is the following:

$$\begin{bmatrix} Y_1 \\ Y_2 \\ Y_3 \end{bmatrix} = \begin{bmatrix} 1 & -1 & 1 \\ 1 & 0 & -2 \\ 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} a \\ b \\ c \end{bmatrix} + \begin{bmatrix} e_1 \\ e_2 \\ e_3 \end{bmatrix},$$

where a is the intercept, b is the linear coefficient, and c is the quadratic coefficient (46).

When there are three time points, the estimates of the regression coefficients reduce to:

$$\begin{bmatrix} \hat{a} \\ \hat{b} \\ \hat{c} \end{bmatrix} = \begin{bmatrix} \hat{N}_1^2 + \hat{N}_2^2 + \hat{N}_3^2 & -\hat{N}_1^2 + \hat{N}_3^2 & \hat{N}_1^2 - 2\hat{N}_2^2 + \hat{N}_3^2 \\ -\hat{N}_1^2 + \hat{N}_3^2 & \hat{N}_1^2 + \hat{N}_3^2 & -\hat{N}_1^2 + \hat{N}_3^2 \\ \hat{N}_1^2 - 2\hat{N}_2^2 + \hat{N}_3^2 & -\hat{N}_1^2 + \hat{N}_3^2 & \hat{N}_1^2 + 4\hat{N}_2^2 + \hat{N}_3^2 \end{bmatrix}^{-1} \begin{bmatrix} \hat{N}_1^2 \hat{Y}_1 + \hat{N}_2^2 \hat{Y}_2 + \hat{N}_3^2 \hat{Y}_3 \\ -\hat{N}_1^2 \hat{Y}_1 + \hat{N}_3^2 \hat{Y}_3 \\ \hat{N}_1^2 \hat{Y}_1 - 2\hat{N}_2^2 \hat{Y}_2 + \hat{N}_3^2 \hat{Y}_3 \end{bmatrix}$$

When the \hat{N}_i^2 's do not vary much, the equation simplifies to:

$$\begin{bmatrix} \hat{a} \\ \hat{b} \\ \hat{c} \end{bmatrix} = \begin{bmatrix} 3 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 6 \end{bmatrix}^{-1} \begin{bmatrix} \hat{Y}_1 + \hat{Y}_2 + \hat{Y}_3 \\ -\hat{Y}_1 + \hat{Y}_3 \\ \hat{Y}_1 - 2\hat{Y}_2 + \hat{Y}_3 \end{bmatrix}.$$

In this simple case, the least-squares estimated effects are:

$$\text{Linear: } \hat{b} = (\hat{Y}_3 - \hat{Y}_1) / 2 \text{ and}$$

$$\text{Quadratic: } \hat{c} = (\hat{Y}_1 + \hat{Y}_3 - 2\hat{Y}_2) / 6.$$

Expressing the regression coefficients \hat{b} and \hat{c} in terms of the differences d_1 and d_2 :

$$\hat{b} = (d_1 + d_2) / 2, \text{ and } \hat{c} = (d_1 - d_2) / 6$$

shows that testing $b = 0$ and $c = 0$ is equivalent to testing:

$$H_4: D_1 + D_2 = 0 \text{ vs } D_1 + D_2 \neq 0 \text{ and}$$

$$H_5: D_1 - D_2 = 0 \text{ vs } D_1 - D_2 \neq 0.$$

The individual two-sided tests, (unadjusted for multiple testing) are:

$$\text{Reject } H_4 \text{ if } |d_1 + d_2| > z_{\frac{\alpha}{2}} \sqrt{\sigma_1^2 + \sigma_2^2 + 2\sigma_{12}} \text{ and}$$

$$\text{Reject } H_5 \text{ if } |d_1 - d_2| > z_{\frac{\alpha}{2}} \sqrt{\sigma_1^2 + \sigma_2^2 - 2\sigma_{12}}.$$

Note that the individual hypotheses and tests, H_3 and H_4 are identical to each other.

In the polynomial regression setting one is not interested in testing whether the intercept is zero, only whether the linear or quadratic terms equal zero. Because only two tests are of concern, the Bonferroni adjustment requires using $\alpha/4$ instead of the $\alpha/6$ used for the three pairwise difference tests.

Orthogonal polynomial contrasts

Use of orthogonal polynomial contrasts to assess nonlinear trends as implemented in SUDAAN's PROC DESCRIPT (see the example in section 16.6.9.4 of the SUDAAN 11, Language Manual) (16) is illustrated here.

The linear and quadratic orthogonal contrasts for the case of three equally-spaced time points are the following:

$$\text{Linear contrast} = -\hat{Y}_1/2 + \hat{Y}_3/2 \text{ and Quadratic contrast} = \hat{Y}_1/4 - \hat{Y}_2/2 + \hat{Y}_3/4.$$

Expressing the orthogonal contrasts in terms of the differences d_1 and d_2 shows their equivalence to the regression coefficients \hat{b} and \hat{c} from the polynomial regression model above:

$$\text{Linear contrast} = -(d_1 + d_2)/2 = \hat{b} \text{ and}$$

$$\text{Quadratic contrast} = (d_1 - d_2)/4 = \hat{c}.$$

Thus, when the sample is large and the population is stable over time, using orthogonal polynomial contrasts to test whether the linear and quadratic effects are zero is approximately the same as testing hypotheses H_4 and H_5 , respectively. As for polynomial regression, only two tests are being made, so the Bonferroni adjustment requires using $\alpha/4$ instead of the $\alpha/6$ used for the three pairwise difference tests.

Generating orthogonal polynomial contrast coefficients. For analyses of record-level survey data using SUDAAN software, the POLYNOMIAL statement in PROC DESCRIPT or PROC RATIO can be used to compute and test orthogonal contrasts. CONTRAST statements also can be used with the contrast coefficients explicitly specified to produce polynomial orthogonal contrasts. When the observed time points are not equally spaced, the CONTRAST statements with specially generated orthogonal polynomial contrast coefficients must be used (24). SAS PROC IML can generate the contrast coefficients for unequally spaced time points which can then be used in the CONTRAST statement in SUDAAN's PROC DESCRIPT (14–16).

Appendix IV. Joinpoint Regression: What it is and how to Parameterize a Model

Joinpoint regression (also referred to as piecewise regression, segmented regression, or linear spline regression) characterizes trends by fitting a model consisting of two or more linear segments that have different slopes and are connected at the time point or points where a change in trend occurs (referred to as joinpoints, change points, or knots) (25,36,37). The model can be parameterized so that the joinpoints are located at or between the observed time points. As discussed in [Issue 11](#), when conducting trend analyses using NCHS data, it is recommended that joinpoints be located at observed time points. In general, the line segments of a joinpoint model connect at the joinpoints under the assumption that there is no discontinuity or “jump” in the outcome measure (e.g., rates and percentages). This assumption is considered to be appropriate for NCHS data, with a few exceptions. For example, when there is a change in the ICD version used to code mortality data, changes in the classification of causes of death result in discontinuities, as reflected in the comparability ratios that are computed for cause-of-death categories. For survey data, a discontinuity due to lack of comparability could occur for certain subgroups or variables when there is a change in the survey design.

Joinpoint regression models are frequently used for trend analyses of NCHS data because they provide an easily interpretable characterization of nonlinear trends, produce estimates of change during specified time periods, and allow tests of change in trend. When describing the trend resulting from a joinpoint regression model, the analyst should reference each line segment of the trend, as follows: the beginning line segment of a joinpoint regression model begins at the first observed time point and extends to the first joinpoint. Line segments in the middle of the time period extend from the earlier joinpoint to the next, and the ending line segment extends from the last joinpoint to the last observed time point. For example, if a trend analysis includes data for 1999–2014 and joinpoints are located at 2003 and 2007, then the three segments that comprise the overall trend should be referred to as the trend during 1999–2003, the trend during 2003–2007, and the trend during 2007–2014.

Parameterizing a Joinpoint Regression Model

There are several equivalent ways to parameterize a joinpoint regression model. Two of these are presented below (referred to as Parameterization A and Parameterization B). The SAS and SUDAAN code needed to implement the two parameterizations is provided to assist analysts who will need to run a joinpoint regression model for record-level survey data. Note that when using NCI’s Joinpoint software, the user does not need to parameterize the joinpoint model because the software does this.

Notation

t = the observed time point (year, cycle) indexed as $t=1, 2, 3, \dots, T$,
 x_k = the observed time point at which the k th joinpoint is located, $k = 1, 2, \dots, K$,
 y_{it} = the value of the outcome variable for unit i at time t .

Parameterization A

One parameterization of a joinpoint regression model includes a parameter for the slope of the first line segment and k parameters for the change in slope between the line segments on either side of each of k joinpoints. In Chapter 10: Indicator Variables “Piecewise Regression” (pages 346–348), Neter, et al, (25) present the following specification for such a joinpoint model, with k joinpoints located at times x_1, x_2, \dots, x_k ,

$$E(y_{it}) = \beta_0 + \beta_1 t + \delta_1 (t - x_1) I_{x_1} + \delta_2 (t - x_2) I_{x_2} + \dots + \delta_k (t - x_k) I_{x_k},$$

$$\text{where } I_{x_k} = \begin{cases} 1 & \text{for } t > x_k \\ 0, & \text{otherwise} \end{cases}.$$

The slope of the first line segment is considered to be increasing or decreasing significantly if the test of the null hypothesis that $\beta_1 = 0$ is rejected. If the null hypothesis is not rejected, the slope of the first line segment is considered to be stable within the precision of the test. More generally, under this parameterization, the slope of the $k + 1$ th line segment differs significantly from that of the k th line segment if the test of the null hypothesis that $\delta_k = 0$ is rejected. The slope of the $k+1$ th line segment is increasing or decreasing significantly if the test of the null hypothesis that $\beta_1 + \delta_1 + \dots + \delta_k = 0$ is rejected. If the null hypothesis is not rejected, the slope of the line segment is considered to be stable within the precision of the test.

An equivalent joinpoint regression model specification can be found in Kim, *et al*, equation 1 (36).

Parameterization B

The joinpoint model specification above can be algebraically manipulated to yield a parameterization with parameters for the slopes of each of the $k+1$ line segments.

When there is $k = 1$ joinpoint:

$$E(y_{it}) = \beta_0 + \beta_1 \text{Seg}_1 + \beta_2 \text{Seg}_2$$

$$\text{where, } \text{Seg}_1 = \begin{cases} t & \text{for } t \leq x_1 \\ x_1 & \text{for } x_1 < t \end{cases},$$

$$\text{Seg}_2 = \begin{cases} 0 & \text{for } t \leq x_1 \\ t - x_1 & \text{for } x_1 < t \end{cases}.$$

When there are $k = 2$ joinpoints:

$$E(y_{it}) = \beta_0 + \beta_1 \text{Seg}_1 + \beta_2 \text{Seg}_2 + \beta_3 \text{Seg}_3$$

$$\text{where, } \text{Seg}_1 = \begin{cases} t & t \leq x_1 \\ x_1 & x_1 < t \end{cases},$$

$$\text{Seg}_2 = \begin{cases} 0 & t \leq x_1 \\ t - x_1 & x_1 < t \leq x_2, \\ x_2 - x_1 & x_2 < t \end{cases},$$

$$\text{Seg}_3 = \begin{cases} 0 & t \leq x_2 \\ t - x_2 & x_2 < t \end{cases}.$$

Test of $H_0: \beta_k = 0, K = 1, 2, \dots, k$, assesses whether the slope of the k th line segment is stable, increasing, or decreasing.

Test of $H_0: \beta_{k+1} - \beta_k = 0$, assesses whether the slopes of the k th and $k+1$ th line segments differ.

Data Example 1: Parameterization A with one joinpoint

The annotated SAS and SUDAAN code below fits a joinpoint regression model using Parameterization A described above. The model has one joinpoint and two line segments that connect at the joinpoint.

$$\begin{aligned} \text{MODEL: Dependent variable} &= b_0 + b_1 * \text{TIME} + b_2 * (\text{TIME} - \text{JOINPT1}) * \text{IND1} \\ &= b_0 + b_1 * \text{TIME} + b_2 * \text{CHANGE1} \end{aligned}$$

where, b_0 = intercept of the first line segment,

b_1 = slope of the first line segment,

b_2 = difference between the slopes of the first and second line segments,

TIME = the observed time points (e.g., years, cycles),

JOINPT1 = the location of the first joinpoint,

IND1 = binary variable indicates whether or not the time point falls after the joinpoint,

CHANGE1 = (TIME - JOINPT1) * IND1, so has value = 0 if the time point falls before or on the joinpoint, and value = TIME - JOINPT1 if the time point falls after the joinpoint.

Define IND1 in SAS:

```
IND1 = 0;
```

```
IF TIME > JOINPT1 THEN IND1 = 1;
```

Define CHANGE1 in SAS:

```
CHANGE1 = (TIME - JOINPT1) * IND1;
```

Run the joinpoint regression model in SUDAAN's PROC REGRESS:

```
PROC REGRESS NOTSORTED;
```

```

SUBPOPX specification;
NEST stratum and PSU variables;
WEIGHT sample weight variable;
MODEL dependent variable = TIME CHANGE1;
TESTS waldf satadjchi satadjf;
PRINT /betafmt=f7.4;
run;

```

Hypothesis tests:

If b_1 is statistically significantly different from 0, the slope of the first line segment is increasing (positive slope) or decreasing (negative slope).

If b_2 is statistically significantly different from 0, then the slopes of the first and second line segments differ.

If b_1+b_2 is statistically significantly different from 0, the slope of the second line segment is increasing or decreasing.

Data Example 2: Parameterization A with two joinpoints

The annotated SAS and SUDAAN code below fits a joinpoint regression model using Parameterization A described above. The model has two joinpoints and three line segments that connect at the joinpoints.

```

MODEL: Dependent variable =  $b_0 + b_1*TIME + b_2*(TIME-JOINPT1)*IND1 + b_3*(TIME-JOINPT2)*IND2$ 
      =  $b_0 + b_1*TIME + b_2*CHANGE1 + b_3*CHANGE2$ 

```

where, b_0 = intercept of the first line segment,

b_1 = slope of the first line segment,

b_2 = difference between the slopes of the first and second line segments,

b_3 = difference between the slopes of the second and third line segments,

TIME = the observed time points (e.g., year, cycle),

JOINPT1 = the location of the first joinpoint,

JOINPT2 = the location of the second joinpoint,

IND1 = binary variable that indicates whether or not the time point falls after the first joinpoint,

IND2 = binary variable that indicates whether or not the time point falls after the second joinpoint,

CHANGE1 = $(TIME-JOINPT1)*IND1$, so has value = 0 if the time point falls before or on the first joinpoint, and value = $TIME-JOINPT1$ if the time point falls after the first joinpoint,

CHANGE2 = $(TIME-JOINPT2)*IND2$, so has value = 0 if the time point falls before or on the second joinpoint, and value = $TIME-JOINPT2$ if the time point falls after the second joinpoint.

Define IND1 and IND2 in SAS:

```

IND1= 0;
IF TIME > JOINPT1 THEN IND1 = 1;
IND2 = 0;
IF TIME > JOINPT2 THEN IND2 = 1;

```

Define CHANGE1 and CHANGE2 in SAS:

```

CHANGE1 = (TIME-JOINPT1)*IND1;
CHANGE2 = (TIME-JOINPT2)*IND2;

```

Run the joinpoint regression model in SUDAAN's PROC REGRESS:

```

PROC REGRESS NOTSORTED;
SUBPOPX specification;
NEST stratum and PSU variables;
WEIGHT sample weight variable;
MODEL dependent variable = TIME CHANGE1 CHANGE2;
TESTs waldf satadjchi satadjf;
PRINT /betafmt = f7.4;
run;

```

Hypothesis tests:

If b_1 is statistically significantly different from 0, the slope of the first line segment is increasing (positive slope) or decreasing (negative slope).

If b_2 is statistically significantly different from 0, then the slopes of the first and second line segments differ.

If b_3 is statistically significantly different from 0, then the slopes of the second and third line segments differ.

If $b_1 + b_2$ is statistically significantly different from 0, then the slope of the second line segment is increasing or decreasing.

If $b_1 + b_2 + b_3$ is statistically significantly different from 0, then the slope of the third line segment is increasing or decreasing.

Data Example 3: Parameterization B with one joinpoint

The annotated SAS and SUDAAN code below fits a joinpoint regression model using Parameterization B, an equivalent alternative to Parameterization A. The model has one joinpoint and two line segments that connect at the joinpoint.

MODEL: Dependent variable = $b_0 + b_1 \cdot \text{SEG1} + b_2 \cdot \text{SEG2}$

which can be expanded to:

$$\text{Dependent variable} = b_0 + b_1 \cdot (\text{TIME}(1 - \text{IND1}) + \text{JOINPT1} \cdot \text{IND1}) + b_2 \cdot (\text{TIME} - \text{JOINPT1}) \cdot \text{IND1}$$

For $t \leq \text{JOINPT1}$ this reduces to: $b_0 + b_1 \cdot \text{TIME}$

For $t > \text{JOINPT1}$ this reduces to: $b_0 + b_1 \cdot \text{JOINPT1} + b_2 \cdot (\text{TIME} - \text{JOINPT1})$

where, b_0 = intercept of the first line segment,

b_1 = slope of the first line segment,

b_2 = slope of the second line segment,

TIME = the observed time points (e.g., year, cycle),

JOINPT1 = the location of the first joinpoint,

IND1 = binary variable that indicates whether or not the time point falls after the joinpoint,

SEG1 = TIME if the time point falls before or on the first joinpoint or has value = JOINPT1 if time point falls after the first joinpoint,

SEG2 = 0 if time point falls before or on the first joinpoint and has value = TIME - JOINPT1 if it falls after the first joinpoint.

Define IND1 in SAS:

```
IND1= 0;
```

```
IF TIME > JOINPT1 THEN IND1 = 1;
```

Define SEG1 in SAS:

```
IF TIME <= JOINPT1 THEN SEG1 = TIME;
```

```
ELSE SEG1 = JOINPT1;
```

Define SEG2 in SAS:

```
IF TIME <= JOINPT1 THEN SEG2 = 0;
```

```
ELSE SEG2 = TIME - JOINPT1;
```

Run the joinpoint regression model in SUDAAN's PROC REGRESS:

```
PROC REGRESS NOTSORTED;
```

```
SUBPOPX specification;
```

```
NEST stratum and PSU variables;
```

```
WEIGHT sample weight variable;
```

```
MODEL dependent variable = SEG1 SEG2;
```

```
CONTRAST 0 1 -1; /*tests difference between the two slopes*/
```

```
TESTS waldf satadjchi satadjf;
```

```
PRINT /betafint = f7.4;
```

```
run;
```

Hypothesis tests:

If b_1 is statistically significantly different from 0, the slope of the first line segment is increasing (positive slope) or decreasing (negative slope).

If b_2 is statistically significantly different from 0, the slope of the second line segment is increasing or decreasing.

If $b_1 - b_2$ is statistically significantly different from 0, the slopes of the first and second line segments differ.

Data Example 4: Parameterization B with two joinpoints

The SAS and SUDAAN code below fits a joinpoint regression model using Parameterization B. The model has two joinpoints and three line segments that connect at the joinpoints.

MODEL: Dependent variable = $b_0 + b_1 * \text{SEG1} + b_2 * \text{SEG2} + b_3 * \text{SEG3}$

which can be expanded to:

$$\begin{aligned} \text{Dependent variable} = & b_0 + b_1 * (\text{TIME}(1-\text{IND1}) + \text{JOINPT1} * \text{IND1}) \\ & + b_2 * (\text{TIME}-\text{JOINPT1}) * (\text{IND1}-\text{IND2}) + (\text{JOINPT2}-\text{JOINPT1}) * \text{IND2} \\ & + b_3 * (\text{TIME}-\text{JOINPT2}) * \text{IND2} \end{aligned}$$

For $t \leq \text{JOINPT1}$ this reduces to: $b_0 + b_1 * \text{TIME}$

For $\text{JOINPT1} < t \leq \text{JOINPT2}$ this reduces to: $b_0 + b_1 * \text{JOINPT1} + b_2 * (\text{TIME}-\text{JOINPT1})$

For $t > \text{JOINPT2}$ this reduces to: $b_0 + b_1 * \text{JOINPT1} + b_2 * (\text{JOINPT2}-\text{JOINPT1}) + b_3 * (\text{TIME}-\text{JOINPT2})$

where, b_0 = intercept of the first line segment,

b_1 = slope of the first line segment,

b_2 = slope of the second line segment,

b_3 = slope of the third line segment,

TIME = the observed time points (e.g., year, cycle)

JOINPT1 = the location of the first joinpoint,

JOINPT2 = the location of the second joinpoint,

IND1 = binary variable that indicates whether or not the time point falls after the first joinpoint,

IND2 = binary variable that indicates whether or not the time point falls after the second joinpoint,

SEG1 = TIME if the time point falls before or on the first joinpoint or has value = JOINPT1 if the time point falls after the first joinpoint,

SEG2 = 0 if time point falls before or on the first joinpoint, has value = TIME-JOINPT1 if time point falls

after the first joinpoint and before or on the second joinpoint, and has value = JOINPT2-JOINPT1 if time point falls after the second joinpoint,

SEG3 = 0 if time point falls before or on the second joinpoint and has value = TIME-JOINPT2 if time point falls after the second joinpoint.

Define IND1 and IND2 in SAS:

```
IND1 = 0;
```

```
IF TIME > JOINPT1 THEN IND1 = 1;
```

```
IND2 = 0;
```

```
IF TIME > JOINPT2 THEN IND2 = 1;
```

Define SEG1 in SAS:

```
IF TIME <= JOINPT1 THEN SEG1 = TIME;
```

```
ELSE SEG1 = JOINPT1;
```

Define SEG2 in SAS:

```
IF TIME <= JOINPT1 THEN SEG2 = 0;
```

```
ELSE IF (JOINPT1 < TIME <= JOINPT2) THEN SEG2 = TIME-JOINPT1;
```

```
ELSE IF TIME > JOINPT2 THEN, SEG2 = JOINPT2-JOINPT1;
```

Define SEG3 in SAS;

```
IF TIME <= JOINPT2 THEN SEG3 = 0;
```

```
ELSE SEG3 = TIME-JOINPT2;
```

Run the joinpoint regression model in SUDAAN's PROC REGRESS:

```

PROC REGRESS NOTSORTED;
SUBPOPX specification;
NEST stratum and PSU variables;
WEIGHT sample weight variable;
MODEL dependent variable = SEG1 SEG2 SEG3;
CONTRAST 0 1 -1 0; /*tests difference between the first two slopes*/
CONTRAST 0 0 1 -1; /*tests difference between the second and third slope*/
CONTRAST 0 1 0 -1; /*tests difference between the first and last slopes*/
TESTS waldf satadjchi satadjf;
PRINT /betafmt = f7.4;
run;

```

Hypothesis tests:

If b_1 is statistically significantly different from 0, the slope of the first line segment is increasing (positive slope) or decreasing (negative slope).

If b_2 is statistically significantly different from 0, the slope of the second line segment is increasing or decreasing.

If b_3 is statistically significantly different from 0, the slope of the third line segment is increasing or decreasing.

If $b_1 - b_2$ is statistically significantly different from 0, the slopes of the first and second line segments differ.

If $b_1 - b_3$ is statistically significantly different from 0, the slopes of the first and third line segments differ.

If $b_2 - b_3$ is statistically significantly different from 0, the slopes of the second and third line segments differ.

Appendix V. Calculating a Cochran-Mantel-Haenszel Test for Trend in SUDAAN

The SUDAAN 11 Language Manual details the general form for the stratum-adjusted Cochran-Mantel-Haenszel Test for Trend (CMHT) and the ANOVA-type alternative (ACMH) test statistics for $I \times R \times C$ tables (where I is the number of analytic strata, R is the number of categories of the row variable Y , and C is the number of categories of the column variable X) (16). These tests, which assume that the row variable Y and column variable X are ordinal, are sensitive to a linear association between X and Y in each analytic stratum. The alternative hypothesis is that, for at least one of the analytic strata, the mean scores of the R rows are unequal. SUDAAN uses a modified CMHT statistic that is more specific to a test for trend, as opposed to a test of independence (which is the usual CMHT). For more details, see section 7.5.2 in Agresti's *Categorical Data Analysis* (33).

The following algebra illustrates how the test works for the simple case of one analytic stratum, a binary outcome variable Y , and the column variable X representing T years. Here, the CMHT result is compared with that obtained from testing the slope from a linear regression model fit to the trend. The reader will need to be familiar with section 14.9.3.3 of the SUDAAN 11 Language Manual (16) to follow the development of this appendix.

Example

The example provided below has one analytic stratum, two rows (the two categories of the binary outcome variable Y), and c columns (the observed time points). Row 1 contains the estimated number of positive responses and Row 2 contains the estimated number of negative responses of the binary outcome.

Notation

Some of the notations used in other appendices of these guidelines are used in the SUDAAN Language Manual to reference different statistics. When this occurs, a left subscript "S" is used for the SUDAAN variables shown below to avoid confusion. Note, the right subscript "1" on variables below refers to analytic stratum "1."

\hat{N}_{irc} , is the estimated population in row r and column c of the R by C table for the i th analytic stratum,

N_c is the population total for year c ,

$\hat{N}_c = \sum_i w_{ci}$, the estimate of the population total, N_c , for year c ,

$\hat{Y}_c = \frac{\sum_i w_{ci} Y_{ci}}{\hat{N}_c}$, the estimate of population prevalence, \bar{Y} , for time c ,

$\bar{Y} = \frac{\sum_{t=1}^C N_t \bar{Y}_t}{\sum_{t=1}^C N_t}$. Is the population prevalence across the c years,

$\hat{\bar{Y}} = \frac{\sum_{t=1}^C \hat{N}_t \hat{Y}_t}{\sum_{t=1}^C \hat{N}_t}$, the estimate of population prevalence \bar{Y} , and

$\hat{t} = \sum_{t=1}^T t \hat{N}_t / \sum_{t=1}^T \hat{N}_t$ is the estimated average year over the population (i.e., $\sum_{t=1}^T t N_t / \sum_{t=1}^T N_t$).

In the SUDAAN Language Manual, each stratum-specific $R \times C$ table is rearranged so that the rows are strung out in one long vector. For this example which has one analytic stratum, this vector is:

$${}_s \hat{N}'_1 = (\hat{N}_1 \hat{Y}_1, \dots, \hat{N}_c \hat{Y}_c, \hat{N}_1 (1 - \hat{Y}_1), \dots, \hat{N}_c (1 - \hat{Y}_c)).$$

The vector, e'_1 , specified in the SUDAAN manual, denotes the expected values of ${}_s \hat{N}'_1$ under the row/column independence assumption of contingency tables, so that, in this case:

$${}_s e'_1 = (N_1 \bar{Y}, \dots, N_c \bar{Y}, N_1 (1 - \bar{Y}), \dots, N_c (1 - \bar{Y})),$$

For this example:

$$R_1 = [1, -1] \text{ and}$$

$C_1 = (x_1, \dots, x_c)$, denotes a particular interval scoring of the ordinal categories.

Because ${}_s B_1 = R_1 \otimes C_1 = [x_1, \dots, x_c, -x_1, \dots, -x_c]$, in this case:

$$\begin{aligned} G &= {}_s B_1 \left({}_s \hat{N}_1' - {}_s e_1' \right) \\ &= [x_1, \dots, x_c, -x_1, \dots, -x_c] \left(\begin{bmatrix} \hat{N}_1 \hat{Y}_1 \\ \vdots \\ \hat{N}_c \hat{Y}_c \\ \hat{N}_1 (1 - \hat{Y}_1) \\ \vdots \\ \hat{N}_c (1 - \hat{Y}_c) \end{bmatrix} - \begin{bmatrix} N_1 \bar{Y} \\ \vdots \\ N_c \bar{Y} \\ N_1 (1 - \bar{Y}) \\ \vdots \\ N_c (1 - \bar{Y}) \end{bmatrix} \right) \\ &= \sum_{t=1}^c x_t \hat{N}_t \hat{Y}_t - \sum_{t=1}^c x_t N_t \bar{Y} - \sum_{t=1}^c x_t \hat{N}_t (1 - \hat{Y}_t) + \sum_{t=1}^c x_t N_t (1 - \bar{Y}). \end{aligned}$$

When the \hat{N}_c 's and \hat{Y} are used to estimate $N_t \bar{Y}$ and $N_t (1 - \bar{Y})$ are provided, the estimate of G is the statistic:

$$\hat{G} = 2 \sum_{t=1}^c x_t \hat{N}_t (\hat{Y}_t - \hat{Y})$$

As shown below, \hat{G} is close to \hat{B}_1 , the estimate of slope from Method 1 in [Appendix I](#) (equation 1):

Subtracting the zero term, $\frac{\sum_{t=1}^T \hat{N}_t \hat{Y} (t - \hat{t})}{\sum_{t=1}^T \hat{N}_t (t - \hat{t})^2} = 0$, from \hat{B}_1 , it can be seen that,

$$\hat{B}_1 = \frac{\sum_{t=1}^T \hat{N}_t (\hat{Y}_t - \hat{Y}) (t - \hat{t})}{\sum_{t=1}^T \hat{N}_t (t - \hat{t})^2} \text{ and that, } \frac{\sum_{t=1}^T \hat{N}_t (\hat{Y}_t - \hat{Y}) \hat{t}}{\sum_{t=1}^T \hat{N}_t (t - \hat{t})^2} = 0,$$

Thus,

$$\hat{B}_1 = \frac{\sum_{t=1}^T \hat{N}_t (\hat{Y}_t - \hat{Y}) t}{\sum_{t=1}^T \hat{N}_t (t - \hat{t})^2}.$$

Thus, it can be seen that \hat{G} and \hat{B}_1 are related as follows:

$$\hat{B}_1 = \frac{\frac{1}{2} \hat{G}}{\sum_{t=1}^T \hat{N}_t (t - \hat{t})^2}.$$

This shows that these two test statistics are very close. A test of no trend using either statistic should yield similar or even identical results (depending on the variance approximations used by SUDAAN).

Appendix VI. Transforming Proportions to Log-Odds Scale

Logistic regression often is used to model a time trend for survey data when the outcome variable is binary. If the trend is nonlinear and Joinpoint software is used to identify the number and location of joinpoints, it is preferable to transform the proportions and standard errors input into the Joinpoint program to the log-odds scale. This transformation can be achieved as follows and as described on page 32 of Cox's *The Analysis of Binary Data* (29):

- 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, $\widehat{se}(\hat{p})$, as follows:

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

Input the transformed proportions and their transformed standard errors into the Joinpoint software and fit a linear model to identify the number and location of joinpoints. A logistic model with the indicated joinpoints can be constructed and fit to the record-level data using SUDAAN or other survey analysis software.

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