2016 NATIONAL SURVEY ON DRUG USE AND HEALTH

METHODOLOGICAL RESOURCE BOOK SECTION 13: STATISTICAL INFERENCE REPORT

Substance Abuse and Mental Health Services Administration
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2016 NATIONAL SURVEY ON DRUG USE AND HEALTH: STATISTICAL INFERENCE REPORT

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1. Introduction

Statistical inference occurs whenever data obtained from sample observations belonging to and considered representative of a larger target population are used to make generalizations concerning the larger population. The target population for the 2016 National Survey on Drug Use and Health (NSDUH)[1] was the U.S. civilian, noninstitutionalized population aged 12 or older (at the time of their interview) in 2016. Measurements for this target population were the responses to the survey questions provided by people participating in the 2016 survey. Examples of conducting statistical inference include using the weighted estimate and the corresponding standard error of the number of users of illicit drugs[2] based on a sample to make a statement about the number of users in the U.S. civilian, noninstitutionalized population. Another example is conducting a significance test to determine whether the percentage of adults with serious mental illness (SMI) increased over time.

Statistical inferences concerning characteristics of interest for this population and various subpopulations are presented in the form of estimates (number of people and associated prevalence estimates) derived from the sample data collected. Examples of the inferences made from the 2016 NSDUH data are presented in the 2016 detailed tables[3] (Center for Behavioral Health Statistics and Quality [CBHSQ], 2017f) for youths aged 12 to 17 and adults aged 18 or older on drug, alcohol, and tobacco use, as well as substance use disorder (SUD) (also referred to as dependence or abuse), treatment, health topics, and alcohol consumption. For youths, topics include youth experiences and measures on mental health service utilization, major depressive episode (MDE), and treatment for depression (among youths with MDE). For adults, topics include measures on any mental illness (AMI), SMI, AMI excluding SMI, mental health service utilization (i.e., treatment or counseling for mental health issues), suicidal thoughts and behaviors, MDE, treatment for depression (among adults with MDE), and serious psychological distress (SPD). Measures such as risk and availability of substance use and the co-occurrence of mental disorders with substance use or with SUDs also are presented for adults and youths.

For the 2016 NSDUH, various measures of interest included in the detailed tables were also presented in three national-level first findings reports (FFRs) on the following topics:[4] key substance use and mental health indicators in the United States (CBHSQ, 2017c), receipt of services for substance use and mental health issues among adults (Park-Lee, Lipari, Hedden, Kroutil, & Porter, 2017), and risk and protective factors and estimates of substance use initiation (Lipari, Ahrnsbrak, Pemberton, & Porter, 2017).

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[1] Before 2002, the survey was called the National Household Survey on Drug Abuse (NHSDA).

[2] NSDUH obtains information on the following 10 categories of drugs: marijuana, cocaine (including crack), heroin, hallucinogens, inhalants, and methamphetamine, as well as the misuse of prescription pain relievers, tranquilizers, stimulants, and sedatives. Estimates of "illicit drug use" reported from NSDUH reflect the use of drugs in any of these 10 categories.

[3] Starting with the 2015 NSDUH, the mental health detailed tables were combined with the detailed tables on substance use and other measures.

[4] These three reports contain varying topics of interest and have replaced the national findings and mental health findings reports that were published in years before 2014.

The focus of this report is to describe the statistical inference procedures used to produce design-based estimates as presented in the 2016 detailed tables and the 2016 FFRs.[5] Although the examples in this report are based on data before the 2016 NSDUH, the examples remain relevant to the 2016 detailed tables and 2016 FFRs.[6] The statistical procedures and information found in this report can also be generally applied to analyses based on the public use file.[7] To emphasize key points for analyzing NSDUH data, certain sentences throughout this report have been italicized. This report is organized as follows: Section 2 provides background information concerning the 2016 NSDUH survey design, the 2015 survey redesign, and the 2016 questionnaire changes; Section 3 discusses the prevalence estimates and how they were calculated, including specifics on topics such as MDE, SPD, mental illness, SUD, substance use treatment, and perceptions of risk and availability; Section 4 briefly discusses how missing item responses of variables that are not imputed may lead to biased estimates; Section 5 discusses sampling errors and how they were calculated; Section 6 describes degrees of freedom and how they were used when comparing estimates; and Section 7 discusses how the statistical significance of differences between estimates was determined. Section 8 discusses confidence interval estimation, and Section 9 describes how past year initiation of drug use was computed. Finally, Section 10 discusses the conditions under which estimates with low precision were suppressed. Appendix A contains examples that demonstrate how to conduct various statistical procedures documented within this report. Examples include using SUDAAN® Software for Statistical Analysis of Correlated Data (RTI International, 2012) with auxiliary SAS® code (SAS Institute, 2017). In addition to the SUDAAN code, corresponding Stata® software (StataCorp, 2015) examples are included for all exhibits, as well as SAS code using survey analysis procedures for estimating means, totals, and standard errors and applying standard suppression rules.

[5] The 2016 detailed tables and 2016 FFRs are based on the restricted-use data; thus, users of the public use data (CBHSQ/Substance Abuse and Mental Health Services Administration [SAMHSA], 2017) may find inconsistencies in the variable names referenced in this report, Appendix A, the information presented in Table 5.1 in Section 5, and other specific numbers presented in this report (i.e., degrees of freedom).

[6] The specific estimates shown in examples in this report are based on the 2015 restricted-use dataset that was used to create the 2015 detailed tables (CBHSQ, 2016d), and the 2015 FFRs (CBHSQ, 2016c; Hughes et al., 2016; Lipari, Forsyth, Bose, Kroutil, & McHenry, 2016; Lipari, Williams, Copello, & Pemberton, 2016; Medley et al., 2016; Park-Lee, Lipari, Hedden, Copello, & Kroutil, 2016; Piscopo, Lipari, Cooney, & Glasheen, 2016). Appendix A examples are based on the restricted-use datasets from the 2013 and 2014 NSDUHs showing statistical procedures implemented in the 2014 detailed tables (CBHSQ, 2015c).

[7] NSDUH public use files are available on the Substance Abuse and Mental Health Data Archive, which can be accessed on SAMHSA's website: https://datafiles.samhsa.gov/.

2. Background

The respondent universe for the National Survey on Drug Use and Health (NSDUH) is the civilian, noninstitutionalized population aged 12 or older residing within the 50 states and the District of Columbia. The survey covers residents of households (e.g., individuals living in houses/townhouses, apartments, and condominiums; civilians living in housing on military bases) and individuals in noninstitutional group quarters (e.g., shelters, rooming/boarding houses, college dormitories, migratory workers' camps, halfway houses). Excluded from the survey are individuals with no fixed household address (e.g., homeless and/or transient people not in shelters), active-duty military personnel, and residents of institutional group quarters, such as correctional facilities, nursing homes, mental institutions, and long-term hospitals.

The final respondent sample of 67,942 people for the 2016 NSDUH provides a sufficient sample to create domain estimates for a broad range of ages, other demographic characteristics, geographic characteristics, and socioeconomic categories. Individual observations are weighted so that the weighted sample represents the civilian, noninstitutionalized population aged 12 or older for the nation as a whole and for each state. *The person-level weights in NSDUH are calibrated by adjusting for nonresponse and post-stratifying to known population estimates (or control totals) obtained from the U.S. Census Bureau.* For more information on the person-level sampling weight calibration in the *2016 NSDUH Methodological Resource Book*, see Center for Behavioral Health Statistics and Quality (CBHSQ) (2018b).

2.1 Sample Design

The 2014 through 2017 NSDUHs use a coordinated design. Similar to the 1999 through 2013 surveys, the coordinated 4-year design is state based, with an independent, multistage area probability sample within each state and the District of Columbia. As a result, states are viewed as the first level of stratification and as a variable for reporting estimates. Each state was further stratified into approximately equally populated state sampling regions (SSRs). The number of SSRs varied by state and was related to the state's sample size. SSRs were contiguous geographic areas designed to yield approximately the same number of interviews within a given state.[8] There was a total of 750 SSRs for 2016. Creation of the multistage area probability sample then involved selecting census tracts within each SSR, census block groups within census tracts, and area segments (i.e., a collection of census blocks) within census block groups. Finally, dwelling units (DUs) were selected within segments, and within each selected DU, up to two residents who were at least 12 years old were selected for the interview. If two eligible residents within the same DU were selected, they formed a within-DU pair.

The coordinated design for 2014 through 2017 includes a 50 percent overlap in third-stage units (area segments) within each successive 2-year period from 2014 through 2017. In addition to reducing costs, this designed sample overlap slightly increases the precision of estimates of year-to-year trends because of the expected small but positive correlation resulting

[8] Sampling areas were defined using 2010 census geography. Counts of dwelling units and population totals were obtained from the 2010 decennial census data supplemented with revised population projections from Nielsen Claritas (see http://www.nielsen.com/us/en.html).

from the overlapping area segments between successive survey years. There is no planned overlap of sampled DUs or residents.

The 2014 through 2017 design allocates more interviews to the largest 12 states (compared with the 1999 to 2013 design).[9] For the 2016 NSDUH, the target sample size for the largest 12 states was between 1,500 and 4,560 completed interviews and approximately 960 interviews in each of the remaining 38 states and the District of Columbia (CBHSQ, 2017a). *This design change moved the sample from two state sample size groups (large and small) to essentially five state sample size groups, making the sample sizes more proportional to the state population sizes and improving the precision of NSDUH estimates.* This change also allows for a more cost-efficient sample allocation to the largest states while slightly increasing the sample sizes in smaller states to improve the precision of state estimates by direct methods (by pooling multiple years of data) or by using small area estimation (SAE).[10] Population projections based on the 2010 census, data from the 2006 to 2010 American Community Surveys (ACS), and 2013 population projections from Nielsen Claritas (a market research firm based in California) were used to construct the sampling frame for the 2014 through 2017 NSDUHs. In contrast, projections based on the 2000 census were used in constructing the sampling frame for the 2005 to 2013 NSDUHs.

Similar to the 2005 through 2013 NSDUHs, the first stage of selection for the 2014 through 2017 NSDUHs was census tracts.[11] This stage was included to contain sample segments within a single census tract to the extent possible in order to facilitate merging to external data sources such as the ACS or the National Health Interview Survey. Within each SSR, 48 census tracts[12] were selected with probability proportional to a composite measure of size.[13] Within sampled census tracts, adjacent census block groups were combined as necessary to meet the minimum DU size requirements.[14] One census block group or second-stage sampling unit then was selected within each sampled census tract with probability proportional to population size. Compared with the selection process used for the 2005 through 2013 NSDUHs, the selection of census block groups is an additional stage of selection that was included to facilitate possible

[9] In the 1999 to 2013 design, the eight largest states each had a target sample size of 3,600. The remaining states and the District of Columbia each had a sample size of 900. In 2014, the sample design was modified so that the sample size per state was relatively more proportional to the state population.

[10] SAE is a hierarchical Bayes modeling technique used to make state-level estimates for 14 measures related to substance use and mental health. For the most updated methodology details, see "2014–2015 NSDUH: Model-Based Prevalence Estimates (50 States and the District of Columbia)". In addition to the tables for these 14 measures by age group in the 2014–2015 report, similar tables showing the 2015–2016 estimates are available at https://www.samhsa.gov/data/.

[11] Census tracts are relatively permanent statistical subdivisions of counties and parishes that provide a stable set of geographic units across decennial census periods.

[12] Some census tracts had to be aggregated to meet the minimum DU requirement. In California, Florida, Georgia, Illinois, Michigan, New Jersey, New York, North Carolina, Ohio, Pennsylvania, Texas, and Virginia, this minimum size requirement was 250 DUs in urban areas and 200 DUs in rural areas. In the remaining states and the District of Columbia, the minimum requirement was 150 DUs in urban areas and 100 DUs in rural areas.

[13] The composite measure of size is a weighted population size where the weights are the sampling rates defined for specified age groups.

[14] The minimum DU size requirements for census tracts also were applied to census block groups. The purpose of the minimum DU size is to ensure that each sampled area has a sufficient number of DUs to field two NSDUH samples and one field test.

transitioning to an address-based sampling design in a future survey year. For the third stage of selection, adjacent blocks were combined within each sampled census block group to form area segments.

One area segment was selected within each sampled census block group with probability proportionate to a composite measure of size. Although only 20 segments per SSR were needed to support the coordinated 4-year sample for the 2014 through 2017 NSDUHs, an additional 28 segments per SSR were selected to serve as replacements when segment DUs are depleted and/or support any supplemental studies that the Substance Abuse and Mental Health Services Administration (SAMHSA) may choose to field.[15] Eight sample segments per SSR were fielded during the 2016 survey year. Four of these segments were selected for the 2014 survey and used again in 2015; four were selected for first use in the 2015 survey and used again in the 2016 survey; four more were selected for first use in the 2016 survey and will be used again in the 2017 survey. These sampled segments were allocated equally into four separate samples, one for each 3-month period (calendar quarter) during the year. That is, a sample of addresses was selected from two segments per SSR in each calendar quarter so that field data collection occurred essentially year-round. *The primary objective of the fourth stage of sample selection (listing units) was to select the minimum number of DUs needed in each segment to meet the targeted sample sizes for all age groups.* After DU selections were made, an interviewer visited each selected DU to obtain a roster of all people residing in the DU. Using the roster information obtained from an eligible member of the selected DU, zero, one, or two people were selected for the survey. Compared with selecting one eligible person from each selected DU, the selection of zero, one, or two eligible people allows better control of the age group distribution in order to meet targeted sample sizes. Further, the selection algorithm (a modification of the Brewer [1963, 1975] method for selecting samples of size two [Chromy & Penne, 2002]) provides a mechanism for controlling the number of survey-eligible pairs that are selected. Sampling rates were preset by age group and state. Roster information was entered directly into the electronic screening instrument, which automatically implemented the fifth stage of selection based on the state and age group sampling parameters.

Although the overall sample design remained similar, including the $30 incentive payment for participation, various design elements did change starting with the 2014 NSDUH. Beginning with the 2014 NSDUH redesign, a change was implemented in the allocation of sample by age group. In the 2005 through 2013 NSDUHs, the sample was allocated equally among three age groups: 12 to 17, 18 to 25, and 26 or older. Starting in 2014, the allocation of the NSDUH sample is 25 percent for adolescents aged 12 to 17, 25 percent for adults aged 18 to 25, and 50 percent for adults aged 26 or older. The sample of adults aged 26 or older is further divided into three subgroups: aged 26 to 34 (15 percent), aged 35 to 49 (20 percent), and aged 50 or older (15 percent). These age allocation changes were designed to reflect more closely the actual population distributions by state and age group, so that the precision of estimates overall and for older age groups could be improved. *The sample redesign is not expected to affect the prevalence estimates of outcome variables, but the nature of the design changes is expected to*

[15] Eight segments per SSR are needed to field the 2014 through 2017 NSDUHs (8 segments × 4 years = 32 segments per SSR). For the 2015 through 2017 NSDUHs, half of the segments are carried over from the prior year (4 segments × 3 years = 12 segments per SSR). Thus, 20 unique segments per SSR are needed to field the 4-year sample (32 – 12 = 20).

affect the precision of those estimates. Additionally, changes in the sample design with respect to age group and state necessitated a review of the pair sampling strategy (Chromy & Penne, 2002); therefore, the number of pairs (i.e., two eligible residents within the same DU were selected for the interview) selected for the 2014 through 2017 surveys would be reduced from what was selected in surveys before 2014, but they still yielded the same number of completed interviews.

2.2 2015 Redesign

NSDUH's primary purpose is to measure the prevalence and correlates of substance use and mental health issues in the United States. The computer-assisted interview is organized by section based on the mode of administration, content, and routing logic. The first section of the interview consists of questions about certain demographic characteristics, including birth date (which is used to determine a respondent's age), gender, Hispanic/Latino origin, racial group, and education level (highest grade completed). Respondents are then asked about more sensitive topics (including, but not limited to) substance use, problems associated with substance use, risk and protective factors related to substance use, and mental health issues. Additional demographic questions are then asked to address topics such as immigration, current school enrollment, employment and workplace issues, household characteristics, health insurance coverage, and income.

For the 2015 NSDUH, several changes were made to the questionnaire and data collection procedures. These changes were intended to improve the quality of the data that were collected and to address the changing needs of substance use and mental health policy and research.[16] The NSDUH questionnaire adopted a revised definition of prescription drug misuse, which defined misuse as use in any way not directed by a doctor, including use without a prescription of one's own; use in greater amounts, more often, or longer than told to take a drug; or use in any other way not directed by a doctor. The prescription drug questions for pain relievers, tranquilizers, stimulants, and sedatives were also redesigned to shift the focus from lifetime misuse to past year misuse, and questions were added about any past year prescription drug use, rather than just misuse. A separate section with methamphetamine questions was added, replacing the methamphetamine questions that were previously asked within the context of prescription stimulants. Substantial changes were also made to questions about inhalants, hallucinogens, smokeless tobacco, and binge alcohol use.

These changes led to potential breaks in the comparability of 2015 estimates with estimates from prior years, especially for overall summary measures, such as any illicit drug use; use of illicit drugs other than marijuana; use of hallucinogens, inhalants, and methamphetamine; misuse of psychotherapeutics; binge and heavy alcohol use overall and among females; smokeless tobacco; substance use treatment; perceptions of risk of harm associated with substance use; and perceived availability of substances. Additionally, certain demographic items were changed as part of the partial redesign. Employment questions were moved from the computer-assisted personal interviewing section to the audio computer-assisted self-interviewing section of the questionnaire. Education questions were updated, and new questions were added

[16] The exact changes are documented in the 2015 NSDUH's Office of Management and Budget clearance package and in a summary report (CBHSQ, 2016b). The summary report and the 2015 NSDUH questionnaire are available on the SAMHSA website at https://www.samhsa.gov/data/.

on disability, English-language proficiency, sexual identity and sexual attraction of adults, and military families. Because of these changes in the survey design, these measures were deemed not comparable, and 2014 and prior NSDUH data were not included in the 2015 or 2016 NSDUH reports and tables. For more specific information about each of the 2015 changes, see Sections B.4.1 and B.4.2 in Section B of the 2015 NSDUH methodological summary and definitions (CBHSQ, 2016a). Other topics, such as the mental health topics, did not undergo major changes and therefore are considered comparable.

2.3 2016 Questionnaire Changes

For the 2016 NSDUH, several changes were made to the questionnaire, primarily to improve the quality of its data. Notable changes are summarized as follows along with information regarding the effect of these changes on the 2016 detailed tables (CBHSQ, 2017f). Descriptions of additional changes to the 2016 NSDUH questionnaire can be found in the 2016 questionnaire specifications that are available at https://www.samhsa.gov/data/.

To account for changing popularity and availability of specific prescription drugs, NSDUH has been designed to allow for the addition and removal of specific prescription drugs from year to year.[17] These specific prescription drugs were further categorized into subtypes and presented as such in the detailed tables. The following specific prescription drugs from 2015 were removed because they had been discontinued or were reported infrequently in the 2015 data: Roxicet®, Actiq®, buspirone, hydroxyzine, meprobamate, and Ritalin® SR. Buprenorphine plus naloxone was added to the prescription pain relievers section to provide a generic form of the brand name drug Suboxone®. The impact of these changes was evaluated, and it was determined that the removal and addition of these drugs did not change the comparability of the subtype or overall pain reliever estimates presented in the 2016 detailed tables.

A change was also implemented in the any past year use of prescription pain reliever section where the response option for Tylenol® with codeine 3 or 4 was modified to clarify that this drug was not the same as over-the-counter Tylenol® in order to reduce potential confusion between these two similarly sounding drug names. As expected, there was a reduction in reports of using Tylenol® with codeine 3 or 4. An impact assessment was done that confirmed that estimates of use and misuse of codeine products were not comparable between 2015 and 2016, but estimates for the overall pain reliever category remained comparable. The lack of comparability for codeine products has been noted in the 2016 detailed tables that present estimates for prescription pain relievers, opioids, and prescription psychotherapeutics (CBHSQ, 2017f). See Section C.5 of the 2016 NSDUH methodological summary and definitions (CBHSQ, 2017a) for more details on the prescription drug questionnaire changes.

In 2016, the question about current school enrollment in the Backend Demographics section was reworded to clarify the question for younger respondents. Instead of asking, "Are you now attending or are you currently enrolled in school?" the question was revised to say, "Do you go to school?" The revised question also instructs respondents to answer "yes" if they were "on holiday or break from school, such as spring break or summer vacation, but plan to return

[17] Any specific drug added or removed from the survey affects the drug screener questions and the main drug module questions.

when the break is over." An impact assessment concluded that the percentage of adolescents aged 12 to 17 who reported currently being enrolled in school decreased between 2015 and 2016; however, estimates of current school enrollment data among those aged 18 to 22 that are used in creating the college enrollment estimates are considered comparable between 2015 and 2016.

In addition to the current school enrollment question asked of all respondents, youths are asked about current school enrollment in the NSDUH Youth Experiences section. In 2016, text was added to the question on current school enrollment in the Youth Experiences section to define what is included in the term "school." These current enrollment data from the Youth Experiences section are used in Section 3 (Risk and Availability) of the 2016 detailed tables (CBHSQ, 2017f). After an assessment analysis, it was determined that the additional text had a negligible effect on the resulting data.

To collect more detailed information about driving under the influence of illicit drugs, the 2016 NSDUH was revised to ask respondents who reported past year alcohol use or selected illicit drug use about driving under the influence of selected individual illicit drugs they indicated using. The selected illicit drugs include marijuana, cocaine (including crack), heroin, hallucinogens, inhalants, and methamphetamine. Previously, questions about driving under the influence of illicit drugs did not specify individual drugs and were asked of past year users of illicit drugs including prescription psychotherapeutics. An impact assessment determined that breaks in trends between 2015 and 2016 occurred for all measures of driving under the influence, including the measure of driving under the influence of alcohol.

3. Prevalence Estimates

The national prevalence estimates were computed using a multiprocedure package called SUDAAN® Software for Statistical Analysis of Correlated Data (RTI International, 2012). *The final, nonresponse-adjusted, and poststratified analysis weights were used in SUDAAN to compute unbiased design-based estimates.* Appendix A contains examples that demonstrate how to compute the prevalence estimates as defined below using SUDAAN (Exhibit A.1), Stata® (StataCorp, 2015) (Exhibit A.2), and SAS® (SAS Institute, 2017) (Exhibit A.3).

Prevalence estimates are the proportions of the population who exhibit characteristics of interest (such as substance use). Let $\hat{p}_d$ represent the prevalence estimate of interest for domain *d*. Then $\hat{p}_d$ would be defined as the ratio

$$\hat{p}_d = \frac{\hat{Y}_d}{\hat{N}_d},$$

where $\hat{Y}_d = \sum_{i \in S} w_i \delta_i y_i$ represents the estimated number of people exhibiting the characteristic of interest in domain *d*, $\hat{N}_d = \sum_{i \in S} w_i \delta_i$ represents the estimated population total for domain *d*, *S* represents the sample, w_i represents the analysis weight, δ_i is defined as 1 if the *i*th sample unit is in domain *d* and is equal to 0 otherwise, and y_i is defined as 1 if the *i*th sample unit exhibits the characteristic of interest and is equal to 0 otherwise.

For certain populations of interest, sample sizes may not be adequate to support inferences using only 1 year of survey data. In these cases, estimates can be produced from annual averages based on combined data from 2 or more survey years. The 2016 detailed tables (CBHSQ, 2017f) did not present any combined data, but combined data may be presented in future detailed tables. *The annual averages can be derived by concatenating the data for the respective years and dividing the analysis weights by a factor that varies depending on the number of years of concatenated data (see Exhibits A.1 through A.3).* For example, the weight would be divided by a factor of 2 for 2 years of concatenated data and a factor of 4 for 4 years of concatenated data.

Prevalence estimates are presented in the 2016 detailed tables (Center for Behavioral Health Statistics and Quality [CBHSQ], 2017f) in the form of numbers in thousands and percentages rounded to the nearest tenth of a percent. For percentages, rounding an estimate close to zero to the nearest tenth of a percent, which has not been suppressed per the National Survey on Drug Use and Health (NSDUH) suppression rules (see Section 10), may result in an estimate of 0.0 percent being displayed in a table. Consequently, the corresponding population total presented in thousands may result in a 0 (i.e., 499 or fewer individuals) being displayed in a table. *Thus, users are reminded that a percentage of 0.0 or a number in thousands of 0 are not exact zeros but are unsuppressed, nonzero estimates that should not be interpreted as no respondents in the population of interest.* If an estimate is exactly a 0 value, corresponding to no

respondents in the sample, the percentage and the number in thousands will be suppressed under the NSDUH suppression rule.

3.1 Adult Major Depressive Episode

The past year adult major depressive episode (MDE) estimates shown in the 2016 detailed tables (CBHSQ, 2017f) are based on the full sample as was done in the 2010 to 2014 mental health detailed tables (CBHSQ, 2012a, 2012c, 2013b, 2014c, 2015d) and the 2015 detailed tables (CBHSQ, 2016d). This differs from the 2008 past year MDE estimates shown in the 2008 detailed tables (Office of Applied Studies, 2009a) and the 2009 mental health detailed tables (CBHSQ, 2010), which were based on only the sample of adult respondents who received the World Health Organization Disability Assessment Schedule (WHODAS) questions in the mental health questionnaire module that preceded the adult depression questionnaire module. The analysis of 2008 MDE data was restricted to only the WHODAS half sample because of apparent reporting differences (context effects) between the half sample that was administered the WHODAS and the other half sample of adult respondents who received the Sheehan Disability Scale (SDS) questions (Dean & LeBaron, 2009). Both half samples have issues with context effects not seen in 2007 and previous years because of the revisions to the mental health module preceding the adult depression module. *To address the break in comparability of the adult MDE data beginning in 2008 and to estimate adult MDE based on the full sample of adults from 2008, adjusted versions of lifetime and past year MDE variables for adults were created retroactively for 2005 to 2008.* These variables were adjusted to make MDE estimates from the SDS half sample in 2008 and from all adult respondents for 2005 to 2007 comparable with the MDE estimates based on data from the half sample that received the WHODAS in 2008 and from all adult respondents in later years (2009 onward). *The adjusted data from 2005 to 2008 can be used in conjunction with unadjusted data from later years to estimate trends in adult MDE over the entire period from 2005 onward.* More information about how the statistically adjusted adult MDE variables were created can be found in Section B.4.8 of the 2016 NSDUH methodological summary and definitions (CBHSQ, 2017a) and in the report describing the adjustments (Aldworth, Kott, Yu, Mosquin, & Barnett-Walker, 2012).

The standard analysis weight, ANALWT, was used to generate all estimates of adult MDE in the 2016 detailed tables (CBHSQ, 2017f) and in the first findings report (FFR) on key substance use and mental health indicators in the United States (CBHSQ, 2017c). More information on the analysis weight can be found in Section A.3.4 of the 2016 NSDUH methodological summary and definitions (CBHSQ, 2017a).

3.2 Serious Psychological Distress

The Kessler Psychological Distress Scale (K6) was used to create the serious psychological distress (SPD) variable. Before 2008, the K6 consisted of one set of questions that asked adult respondents about symptoms of psychological distress in the month when they were the most depressed, anxious, or emotionally distressed in the past year. Starting in 2008, the K6 consisted of two sets of questions that asked adult respondents how frequently they experienced symptoms of psychological distress during two different periods: (1) during the past 30 days, and (2) if applicable, the month in the past year when they were at their worst emotionally. Respondents were asked about this second period only if they indicated that there was a month in

the past 12 months when they felt more depressed, anxious, or emotionally stressed than they felt during the past 30 days. Because of this change, past year K6 and SPD estimates from years before 2008 were no longer comparable with estimates from 2008 onward. *To address this comparability issue, adjusted versions of the past year worst K6 total score and past year SPD variables were created for each of the years from 2005 to 2007 to make the 2005–2007 past year K6 scores and past year SPD estimates comparable with their 2008 and subsequent NSDUH counterparts.*

In the 2016 detailed tables (CBHSQ, 2017f), ANALWT was used to generate 2005–2016 estimates of past year SPD and 2008–2016 estimates of past month SPD. The 2016 FFRs (CBHSQ, 2017c; Lipari et al., 2017; Park-Lee et al., 2017) did not present SPD estimates. More information about how the adjusted K6 and SPD variables were created can be found in the report describing these adjustments (Aldworth et al., 2012).

3.3 Mental Illness

The Substance Abuse and Mental Health Services Administration (SAMHSA) has been publishing estimates of the prevalence of past year serious mental illness (SMI) and any mental illness (AMI) among adults aged 18 or older since the release of the 2008 NSDUH national findings report (Office of Applied Studies, 2009b). Originally, estimates were based on a prediction model for mental illness developed using the 2008 data from the Mental Health Surveillance Study (MHSS), which was embedded in the 2008 NSDUH (referred to as the 2008 WHODAS model). Each respondent in a subsample of adults (about 1,500 in 2008) who had completed the NSDUH interview was administered the Structured Clinical Interview for DSM-IV-TR Axis I Disorders, Research Version, Non-patient Edition (SCID-I/NP) (First, Spitzer, Gibbon, & Williams, 2002).[18] For more specific information on the MHSS sample design, see the sample design report in the *2013 NSDUH Methodological Resource Book* (CBHSQ, 2014d).

The 2008 NSDUH included a split sample, in which half the respondents (approximately 750 MHSS respondents) were administered the WHODAS and the other half were administered the SDS. These samples are referred to as the SDS half sample and the WHODAS half sample. Two models were used to predict SMI for 2008, one for each impairment scale (WHODAS and SDS). The 2008 models for SMI were chosen so that estimates from the WHODAS and SDS samples were approximately equal; hence, SMI estimates for 2008 were based on both samples. *The WHODAS model was determined to be a better predictor of SMI than the SDS model; therefore, starting in 2009, only the WHODAS impairment scale was administered in NSDUH and used for estimating all levels of mental illness. Levels of mental illness include SMI, AMI, low (mild) mental illness (LMI), moderate mental illness (MMI), serious or moderate mental illness (SMMI), and AMI excluding SMI; however, not all measures of mental illness are reported each year.*

Although SAMHSA continued to obtain clinical interviews after 2008, estimates of mental illness from the 2009, 2010, and 2011 NSDUHs were originally based on the WHODAS model developed from the 2008 clinical assessment sample (however, these estimates have since

[18] DSM-IV-TR stands for the *Diagnostic and Statistical Manual of Mental Disorders*, 4th Edition, Text Revision (American Psychiatric Association, 2008).

been updated based on a new model; see next paragraph for details). The same model was applied to each year's NSDUH data to provide consistency in mental illness comparisons across the years. Producing a new model each year based on the small annual clinical samples (only 500 interviews in 2009 and 2010) would have resulted in large changes in the model parameters and corresponding prevalence estimates because of sampling error, making it impossible to detect real trends in mental illness over time. Furthermore, an evaluation of the 2008 model, using the 2009 NSDUH clinical data, found that the model could not be significantly improved with the additional 500-case 2009 clinical sample. The clinical follow-up study, which started in 2008 and continued until 2012, led to a nationally representative sample of approximately 5,000 cases assigned to the WHODAS questions that were used to develop an improved mental illness prediction model (referred to as the 2012 WHODAS model). This revised and improved model was used for estimating all levels of mental illness starting with the 2012 NSDUH and incorporates the NSDUH respondent's age and indicators of past year suicidal thoughts and depression, along with the variables that were specified in the 2008 model (e.g., variables for the K6 scale and the WHODAS), leading to more accurate estimates of mental illness (see below for details on the 2012 model and revised methodology).

For the 2012 through 2016 detailed tables (CBHSQ, 2013b, 2014c, 2015d, 2016d, 2017f),[19] the 2008 and later year mental illness estimates were based on the revised model. As of October 2013, the 2008 to 2011 detailed tables (Office of Applied Studies, 2009a; CBHSQ, 2010, 2012a, 2012c) containing estimates for past year mental illness for adults have been revised based on the 2012 model because the estimates were initially based on the 2008 model. *Thus, long-term trends are available for mental illness measures from the 2008 NSDUH and onward.*

For detailed information on model revisions to the mental illness items, see Section B.4.7 in Appendix B of the 2016 methodological summary and definitions (CBHSQ, 2017a). The SMI measure available for years before 2004 is not comparable with the SMI measure based on the 2012 model, which was the case for the 2008 model SMI measures as well. No mental illness measures are available for the 2004 NSDUH. It should also be noted that there are limitations to the analyses of the mental illness variables that are based on the 2012 prediction model. For more information on this, see the "Using Mental Illness Variables in Analysis" section below.

2012 SMI Prediction Model

The 2012 model is a prediction model for mental illness, and it was used to predict SMI and to estimate prevalence of SMI for the 2016 NSDUH. The prediction model is a weighted logistic regression. The response variable Y was defined so that $Y = 1$ when an SMI diagnosis was positive based on the clinical interview; otherwise, $Y = 0$. If $\mathbf{X}$ is a vector of realized explanatory variables, then the response probability $\pi = \Pr(Y = 1 \mid \mathbf{X})$ can be estimated using a weighted logistic regression model. Further technical details on the 2012 prediction models and the impact of the revised model on the 2008–2011 estimates are available in other reports (see the *2012 Mental Health Surveillance Study: Design and Estimation Report* [CBHSQ, 2014a],

[19] Mental health detailed tables were published separately for the 2009 to 2014 NSDUHs. The mental health and substance use detailed tables were combined starting with the 2015 NSDUH.

Section B.4.7 in Appendix B of the 2016 methodological summary and definitions [CBHSQ, 2017a], or the report on revisions to the 2008 estimation procedures [CBHSQ, 2015b]).

The 2012 SMI prediction model was fit with data from 4,912 WHODAS MHSS respondents from 2008 through 2012, excluding one case from 2008 and one case from 2009 that were dropped because of data errors. The final WHODAS calibration model for the 2012 prediction model for SMI was determined as

$$\text{logit}(\hat{\pi}) = \log[\hat{\pi}/(1-\hat{\pi})] = -5.972664 + 0.0873416X_k + 0.3385193X_w + 1.9552664X_s + 1.1267330\,X_m + 0.1059137X_a \quad (1)$$

or

$$\hat{\pi} = \frac{1}{1+\exp[-(-5.972664 + 0.0873416X_k + 0.3385193X_w + 1.9552664X_s + 1.1267330\,X_m + 0.1059137X_a)]},$$

where $\hat{\pi}$ refers to the estimate of the SMI response probability π. The covariates in equation (1) came from the main NSDUH interview data:

X_k = *Alternative Past Year K6 Score*: Past year K6 score of less than 8 recoded as 0; past year K6 score of 8 to 24 recoded as 1 to 17.

X_w = *Alternative WHODAS Score*: WHODAS item score of less than 2 recoded as 0; WHODAS item score of 2 to 3 recoded as 1, then summed for a score ranging from 0 to 8.

X_s = *Serious Thoughts of Suicide in the Past Year*: Coded as 1 if "yes"; coded as 0 otherwise.

X_m = *Past Year MDE*: Coded as 1 if the criteria for past year MDE were met;[20] coded as 0 otherwise.

X_a = *Recoded Age*: Coded as age minus 18 if aged 18 to 30; coded as 12 otherwise.

A cut point probability π_0 was determined, so that if $\hat{\pi} \geq \pi_0$ for a particular respondent, then he or she was predicted to be SMI positive; otherwise, he or she was predicted to be SMI negative. The cut points were chosen so that the weighted numbers of false positives and false negatives in the MHSS dataset were as close to equal as possible. The predicted SMI status for all adult NSDUH respondents was used to compute prevalence estimates of SMI. In the 2012 SMI WHODAS prediction model, the respondent is classified as having past year SMI if the predicted probability of SMI is greater than or equal to 0.260573529 (SMI cutoff point). A respondent is classified as having past year AMI if the predicted probability of SMI is greater than or equal to 0.0192519810 (AMI cutoff point). See Table 3.1 for the model specifications. Table 3.2 contains the cutoff points for other mental illness levels.

[20] In this situation, the past year MDE measure is from the main NSDUH interview (i.e., not from the SCID-I/NP). See Section B.4.8 of the 2016 NSDUH methodological summary and definitions (CBHSQ, 2017a).

Additional levels of mental illness are created using a combination of the defined mental illness measures. These additional levels include moderate (MMI), mild (low), and AMI excluding SMI. Respondents were defined as having past year MMI if they were classified as having SMMI but classified as not having SMI. Respondents were defined as having past year LMI if they were classified as having AMI but classified as not having SMMI. Please note that MMI and LMI are no longer shown in the detailed tables starting with the 2016 NSDUH. Respondents were defined as having past year AMI excluding SMI if they were classified as having LMI or MMI. In some documentation, AMI excluding SMI is referred to as mild (low) or moderate mental illness (MMI).

Modified 2012 Model for the 2008 SDS Half Sample

As noted previously, the 2008 NSDUH data included a split sample. Similar to the 2008 model, the revised 2012 model also has an alternative model for the SDS data that was fit with data from the complete 2008–2012 MHSS clinical sample that contains 5,653 MHSS respondents, excluding 4 cases from 2008 (1 from the WHODAS half sample and 3 from the SDS half sample) and 1 case from 2009 that were dropped because of data errors.

The modified 2012 SMI prediction model for the SDS half sample was

$$\text{logit}(\hat{\pi}) = \log[\hat{\pi} / (1-\hat{\pi})] = -5.7736246 + 0.1772067X_k + 1.8392433X_s + 1.6428623X_m + 0.1231266X_a \qquad (2)$$

or

$$\hat{\pi} = \frac{1}{1+\exp[-(-5.7736246 + 0.1772067X_k + 1.8392433X_s + 1.6428623X_m + 0.1231266X_a)]}.$$

All of the covariates in equation (2) also appeared in equation (1).

Similar to the WHODAS model, a cut point probability π_0 was determined, so that if $\hat{\pi} \geq \pi_0$ for a particular respondent, then he or she was predicted to be SMI positive; otherwise, he or she was predicted to be SMI negative. The cut points were chosen so that the weighted numbers of false positives and false negatives in the MHSS dataset were as close to equal as possible. In the 2012 SMI SDS half sample prediction model, the respondent is classified as having past year SMI if the predicted probability of SMI is greater than or equal to 0.236434 (SMI cutoff point). Although the SDS half sample prediction model was fit across all years and the cutoff points were determined based on all years, the cutoff points were used only for the main study respondents in the 2008 SDS sample B to predict the SMI positives. See Tables 3.1 and 3.2.

Table 3.1 Final SMI Prediction Models in the 2008–2012 MHSS

	Beta	Beta SE	*T* Statistic	*P* Value	*df*	Wald *p* Value[1]
WHODAS Sample (2008A–2012)						
Intercept	-5.9726640	0.3201	-18.6586	0.0000		
Alt PY K6	0.0873416	0.0248	3.5247	0.0009	1	0.0009
Alt WHODAS	0.3385193	0.0349	9.7034	0.0000	1	0.0000
PY Suicidal Thoughts	1.9552664	0.2164	9.0342	0.0000	1	0.0000
PY MDE	1.1267330	0.2196	5.1308	0.0000	1	0.0000
Age1830	0.1059137	0.0244	4.3380	0.0001	1	0.0001
WHODAS and SDS Samples (2008–2012)[2]						
Intercept	-5.7736246	0.3479	-16.5960	0.0000		
Alt PY K6	0.1772067	0.0190	9.3251	0.0000	1	0.0000
PY Suicidal Thoughts	1.8392433	0.1941	9.4781	0.0000	1	0.0000
PY MDE	1.6428623	0.2119	7.7528	0.0000	1	0.0000
Age1830	0.1231266	0.0259	4.7482	0.0000	1	0.0000

2008A = 2008 WHODAS half sample; Age1830 = recoded age variable; Alt = alternative; *df* = degrees of freedom; K6 = six-item Kessler Psychological Distress Scale; MDE = major depressive episode; MHSS = Mental Health Surveillance Study; PY = past year; SE = standard error; SDS = Sheehan Disability Scale; SMI = serious mental illness; WHODAS = eight-item World Health Organization Disability Assessment Schedule.

[1] The Wald *p* value is obtained from the overall model fitting.

[2] The model is fit over the WHODAS and SDS samples in 2008–2012 but is used only to produce predictions for the 2008 SDS sample.

Source: SAMHSA, Center for Behavioral Health Statistics and Quality, National Survey on Drug Use and Health, 2008–2012.

Table 3.2 Cut Point Probabilities for SMI, AMI, and SMMI, by 2012 Model

	Cut Point Probability
WHODAS Sample (2008A–2012)	
SMI	0.260573529000
AMI	0.019251981000
SMMI	0.077686285365
WHODAS and SDS Samples (2008–2012)[1]	
SMI	0.236434000
AMI	0.019182625
SMMI	0.066163980

2008A = 2008 WHODAS half sample; AMI = any mental illness; SDS = Sheehan Disability Scale; SMI = serious mental illness; SMMI = serious or moderate mental illness; WHODAS = World Health Organization Disability Assessment Schedule.

[1] The model is fit over the WHODAS and SDS samples in 2008–2012, but the cut point predictions are used only to produce predictions for the 2008 SDS sample.

Source: SAMHSA, Center for Behavioral Health Statistics and Quality, National Survey on Drug Use and Health, 2008–2012.

Weights Used for Estimates of Mental Illness

For the 2008 NSDUH, although SMI data for both half samples (SDS and WHODAS) could be analyzed together when using the 2008 model, the AMI, SMMI, LMI, MMI, and AMI excluding SMI data from the two half samples could not be combined for analysis. Under the 2012 model, both the 2008 half samples can be combined to analyze SMI and the other levels of

mental illness because the 2012 models were generated so the estimates would be comparable between the two half samples.

Mental illness measures (e.g., SMI, AMI, SMMI, and AMI excluding SMI)[21] *that are defined based on the 2012 model should be analyzed using the standard analysis weight, ANALWT, for all survey years 2008 through 2016.* With the revised 2012 model, the WHODAS and SDS 2008 half samples can be combined to form single estimates and use ANALWT.[22]

Standard Errors for Mental Illness Estimates

For the 2016 detailed tables and the FFRs (CBHSQ, 2017c, 2017f; Lipari et al., 2017; Park-Lee et al., 2017), standard errors (SEs) for mental illness estimates (SMI, AMI, and AMI excluding SMI) were computed using the NSDUH dichotomous variable values without taking into account any variance introduced through using a model based on the clinical subsample data. *This ignores the added error resulting from fitting the 2012 SMI model, which can be very large.* See the *2012 Mental Health Surveillance Study: Design and Estimation Report* (CBHSQ, 2014a) for details. These *conditional* SEs (conditional on the model predictions being correct) are useful when making comparisons across years and across subpopulations within years because the errors due to model fitting are nearly the same across the estimates being compared, and consequently, they roughly cancel each other out.

Using Mental Illness Variables in Analysis

The mental illness measures (e.g., SMI, AMI, AMI excluding SMI) that were defined based on the 2012 model were examined to determine how they were associated with the mental health predictor variables in the 2012 model. It was found that the 2012 model significantly overestimated the proportion of adults aged 18 or older with SMI (and those with AMI) who had suicidal thoughts in the past year and the proportion of adults who had MDE in the past year (as compared with the clinical interview estimates of the same categories). *Therefore, it is recommended that the mental illness measures derived from the 2012 model should not be used when analyzing past year suicidal thoughts, past year MDE, or other associated variables (including past year suicide attempts, suicide plans, medical treatment for suicide attempts, or lifetime MDE). For example, mental illness estimates should not be generated by whether a respondent has serious thoughts of suicide; likewise, it is not recommended to generate serious thoughts of suicide estimates by levels of mental illness. Similarly, it is recommended that model-based mental illness measures should not be used in conjunction with the K6 variables (including SPD) or WHODAS variables in any analyses (CBHSQ, 2014a).* Note that age is a

[21] The mental illness measure for AMI excluding SMI was added during the 2014 NSDUH and is based on the 2012 model. Because AMI excluding SMI is a composite of the LMI and MMI measures, the same analysis issues apply.

[22] This differs from the initial recommendation for analyzing measures of mental illness besides SMI based on the 2008 model. Because of the 2008 split sample, an adjusted mental health sample weight, MHSAMPWT, was created so that the WHODAS and SDS half samples were separately representative of the civilian, noninstitutionalized population aged 18 or older. However, this weight should not be used to analyze 2008 mental illness data based on the 2012 model.

predictor in the mental illness models; however, it is not an issue to show estimates of mental illness by any age group.

3.4 Substance Use Disorders

Because of the changes to the modules for hallucinogens, inhalants, methamphetamine, and prescription psychotherapeutic drugs in the 2015 NSDUH questionnaire, the sets of respondents who were eligible to be asked the questions about substance use disorders (SUDs) also changed. For example, the changes to the prescription drug questions for 2015 affected which respondents were eligible to be asked the SUD questions for prescription drugs because of their reports of misuse in the past year. *Therefore, new baselines started in 2015 for the SUD estimates for hallucinogens, inhalants, methamphetamine, and prescription psychotherapeutic drugs. Trend data are not available for these measures in the 2016 NSDUH reports and tables. New baselines also started in 2015 for illicit drug use disorder and for SUDs related to illicit drug or alcohol use.* However, trend data are available in the 2015 and later NSDUH reports and tables for alcohol use disorders. Trend data also continue to be available for SUDs for marijuana, cocaine, and heroin because these modules did not change in 2015. For more detailed information on how the SUDs are defined and affected from the 2015 survey redesign, see Section B.4.3 of the 2016 NSDUH methodological summary and definitions (CBHSQ, 2017a).

Before the 2015 NSDUH, all dependence or abuse recodes (except nicotine dependence) were created using edited data, and all values of unknown were treated as a "no" response. *Starting with the 2015 NSDUH, the SUD variables where trend was broken because of the questionnaire changes (hallucinogens, inhalants, methamphetamine, prescription pain relievers, prescription tranquilizers, prescription stimulants, and prescription sedatives) had all missing item response data imputed.* Because trends were expected to be broken for these SUD measures because of the questionnaire redesign, a decision was made to implement the modified predictive mean neighborhood (modPMN) procedure for imputation. The imputation process for the SUD variables is described in detail in the 2016 *Methodological Resource Book's* editing and imputation report (CBHSQ, 2018a), and the rationale for using modPMN imputation versus zero-fill imputation for SUD measures is provided in Chapter 10 of the evaluation of imputation methods report (CBHSQ, 2017b).

3.5 Substance Use Treatment

Changes to the modules for hallucinogens, inhalants, methamphetamine, and prescription psychotherapeutic drugs in the 2015 NSDUH might have affected the sets of respondents who were eligible to be asked questions about treatment for substance use. The potentially affected treatment measures include

- the receipt of treatment for illicit drug or alcohol use,
- substances for which respondents last received or were currently receiving treatment,
- the perceived need for treatment for illicit drug or alcohol use in the past 12 months, and
- the specific substances for which respondents perceived a need for treatment in the past 12 months.

Analysis conducted as part of the 2015 NSDUH redesign impact assessment report (RIAR) (CBHSQ, 2017e) indicated no evidence of a break in comparability between 2015 and earlier years for the three overall substance use treatment variables (alcohol use treatment, illicit drug use treatment, alcohol or illicit drug use treatment). However, given the major changes in who is asked the treatment questions based on who answered the substance use sections and the possible effects of the questionnaire redesign on different subgroups and other substance use treatment measures, the 2016 detailed tables (CBHSQ, 2017f) did not show any multiyear trend tables for the substance use treatment measures.[23] Additionally, all treatment estimates have new baselines starting with the 2015 NSDUH.

Note that the presence of a SUD in the past year is an important component for defining individuals as needing treatment for their illicit drug or alcohol use. *Because new baselines began with the 2015 NSDUH for illicit drug use disorder and for SUDs related to illicit drug or alcohol use, analysts should consider analytic goals carefully, before trending the need for treatment measures.* For more information on various types of need for substance treatment, please see Section B.4.4 of the 2016 NSDUH methodological summary and definitions (CBHSQ, 2017a).

3.6 Perceptions of Risk and Availability

Although the questions on perceptions of the risk of harm from using different substances and the perceived availability of specific illicit drugs did not change in the 2015 NSDUH, initial data quality checks on preliminary data showed deviations from the expected trends for these measures. A survey redesign carries the risk that preceding changes to the questionnaire will affect how respondents answer later questions (e.g., context effects; see Section C.6.2 of the 2015 NSDUH methodological summary and definitions [CBHSQ, 2016a]). Another result of a survey redesign are changes in the respondent contact materials, and these changes can affect how respondents answer NSDUH questions. The 2015 NSDUH had no major changes implemented in the contact materials.

These deviations continued to persist in all the 2015 data from all four quarters. It was unclear whether the changes seen in the perceived risk and availability measures can be attributed to questionnaire or other survey changes with the 2015 NSDUH or if these changes reflect true changes in the population. The set of questions preceding the risk and availability module in the questionnaire had undergone several significant changes that could have affected the way in which respondents answered the perceived risk and availability questions. Further analysis of the 2015 data and the first two quarters of the 2016 data, showed a continued deviation from the expected trend based on data before 2015. As a result, the affected risk and availability variables are considered not comparable with similar variables in years before 2015 and therefore were renamed starting with the 2015 NSDUH. The 2014 and prior year estimates

[23] The 2015 RIAR looked at general subpopulations only and did not complete analyses among more specific subpopulations or for other measures in the substance use treatment section. Analytic goals should be considered before pooling or comparing substance use treatment data from 2015 and 2016 with prior years. For more information on specific treatment measures, see Section 5.3 of the 2015 RIAR (CBHSQ, 2017e).

are not shown in the 2016 detailed tables or FFRs (CBHSQ, 2017c, 2017f; Lipari et al., 2017; Park-Lee et al., 2017).

3.7 Decennial Census Effects on NSDUH Substance Use and Mental Health Estimates

As discussed in Section 2, the person-level weights in NSDUH were calibrated to population estimates (or control totals) obtained from the U.S. Census Bureau. For the weights in 2002 through 2010, annually updated control totals based on the 2000 census were used.[24] Beginning with the 2011 weights, however, the control totals from the U.S. Census Bureau are based on the 2010 census. Two investigations were implemented at the national level to assess the effects of using control totals based on the 2010 census instead of the 2000 census. One of these investigations focused specifically on measures of substance use that are used in the 2011 national findings report (CBHSQ, 2012e) and detailed tables (CBHSQ, 2012b), whereas a separate analysis was conducted to evaluate the impact of the weighting changes on mental health estimates in the 2011 mental health findings report (CBHSQ, 2012d) and associated mental health detailed tables (CBHSQ, 2012c). Because the 2015 and 2016 NSDUH estimates are based on weights that were poststratified to population control totals that were in turn based on projections from the 2010 census, 2-year trend comparisons between 2015 and 2016 are not subject to census effects. *However, trends between 2010 (or earlier years) and 2011 (or later years) may be influenced by census effects, especially for particular subgroups (e.g., people reporting two or more races for both investigations, people reporting American Indian or Alaska Native or Native Hawaiian or Other Pacific Islander).* An additional investigation was done at the state level to evaluate the impact of census effects on model-based small area estimation (SAE).

For more information on the impact of decennial census effects on NSDUH substance use direct estimates, see Section B.4.3 in Appendix B of the 2011 national findings report (CBHSQ, 2012e). For more information on the impact of the decennial census effects on NSDUH mental health direct estimates, see Appendix A of the 2011 mental health findings report (CBHSQ, 2012d). For more information on the impact of the decennial census effects on NSDUH model-based small area estimates, see the 2011–2012 NSDUH SAE guide (CBHSQ, 2013a) and, for greater detail, a currently unpublished NSDUH report (CBHSQ, 2014b). Additionally, for more information on the sampling weight calibration in the 2011 NSDUH, see the person-level sampling weight calibration report (Chen et al., 2013).

3.8 Using Revised Estimates for 2006 to 2010

During regular data collection and processing checks for the 2011 NSDUH, data errors were identified. *These errors affected the data for Pennsylvania (2006–2010) and Maryland (2008–2009). Cases with erroneous data were removed from the data files, and the remaining cases were reweighted to provide representative estimates.* The errors had minimal impact on the national estimates and no effect on direct estimates for the other 48 states and the District of

[24] In addition to the standard 2010 analysis weights poststratified to 2000 census control totals, special weights that were poststratified to 2010 census control totals are available on the 2010 NSDUH public use file (CBHSQ/SAMHSA, 2012).

Columbia. In reports where model-based SAE techniques were used, estimates for all states may have been affected, even though the errors were concentrated in only two states. However, in reports that did not use model-based estimates, the only estimates appreciably affected are estimates for Pennsylvania, Maryland, the mid-Atlantic division, and the Northeast region. The 2016 detailed tables and FFRs (CBHSQ, 2017c, 2017f; Lipari et al., 2017; Park-Lee et al., 2017) did not include state-level, model-based, or division-level estimates. However, they did include estimates for the Northeast region. *Estimates for the Northeast region based on 2006–2010 data may therefore differ from previously published estimates.* Tables and estimates based only on 2011 or later data are unaffected by these data errors. All affected tables (i.e., tables with estimates based on 2006–2010 data) contain a note to indicate this to the user.

Caution is advised when comparing estimates from older reports with data from more recent reports that are based on corrected data files. As discussed previously, comparisons of estimates for Pennsylvania, Maryland, the mid-Atlantic division, and the Northeast region are of most concern, whereas comparisons of national data or data for other states and regions are essentially still valid. A selected set of corrected versions of reports and tables has been produced. In particular, a set of modified detailed tables that include revised 2006–2010 estimates for the mid-Atlantic division and the Northeast region for certain key measures has been released. Given the change noted previously, comparisons between unrevised 2006–2010 estimates and estimates based on 2011–2016 data for the areas of most concern are not recommended.

4. Missingness

4.1 Potential Estimation Bias Due to Missingness

In the 2016 National Survey on Drug Use and Health (NSDUH), many variables, including the main drug and various demographic variables, had missing item response values imputed. The imputation process treats the imputed value as a true response and therefore may underestimate the variance, but the difference is small enough to be considered ignorable. See the 2016 NSDUH editing and imputation report (Center for Behavioral Health Statistics and Quality [CBHSQ], 2018a) and the predictive mean neighborhood evaluation report (CBHSQ, 2017b) for further details on the imputation process and the evaluation on the impact of imputation on the variance.

The missing item responses of many other variables were not imputed, and these missing responses may lead to biased estimates in the 2016 detailed tables (CBHSQ, 2017f). In addition, another source of potential uncertainty about some estimates may occur because of the way unknown item responses (e.g., blank, "don't know," "refused") were actually coded for different variables. *For example, some recoded variables (i.e., variables created from one or more source variables) classified unknown item responses in the source variable(s) as missing values, whereas others did not.* See Ruppenkamp, Emrich, Aldworth, Hirsch, and Foster (2006) for further details.

Recall from Section 3 that prevalence estimates are defined as the proportions of the population who exhibit characteristics of interest. Let $\hat{p}_d$ represent the estimated prevalence estimate of interest for domain *d*, with $\hat{p}_d$ defined as

$$\hat{p}_d = \frac{\hat{Y}_d}{\hat{N}_d},$$

where $\hat{Y}_d$ = estimated number of people exhibiting the characteristic of interest in domain *d*, and $\hat{N}_d$ = estimated population total for domain *d*.

The variable defining the characteristic of interest (e.g., illicit drug use) is referred to as the *analysis* variable, and the variable defining the domain of interest (e.g., receipt of past year mental health treatment/counseling) is referred to as the *domain* variable. Suppose that the analysis variable has all its missing values imputed, but the domain variable does not employ the imputation of missing values. In such cases, the estimates $\hat{N}_d$ and $\hat{Y}_d$ may be negatively biased, and the $\hat{p}_d$ estimates also may be biased. To see this, suppose that the domain variable has *D* levels, and define

$$\hat{N} = \sum_{d=1}^{D} \hat{N}_d + \hat{N}_m,$$

where $\hat{N}$ = estimated population total, $\hat{N}_d$ = estimated population total for domain *d*, $d = 1, 2, ..., D$, and $\hat{N}_m$ = estimated population total corresponding to the missing values of the domain variable. Thus, if $\hat{N}_m$ is positive (i.e., there are missing domain-variable responses), then at least one of the $\hat{N}_d$ estimates will be negatively biased. The presence of negative bias in at least one of the $\hat{Y}_d$ estimates can be similarly demonstrated if $\hat{Y}_m$ is positive, where $\hat{Y}_m$ = the estimated number of people exhibiting the characteristic of interest and corresponding to the missing values of the domain variable. *If either of* $\hat{N}_m$ *and* $\hat{Y}_m$ *is positive, then* $\hat{p}_d$ *may be biased by some unknown amount.*

Suppose that instead, the domain variable has all its missing values imputed, but the analysis variable does not employ the imputation of missing values. In such cases, at least one of the $\hat{N}_d$ estimates will be negatively biased. If all missing values for the analysis variable in the domain do not have the condition of interest, $\hat{Y}_d$ would have no bias. Otherwise, $\hat{Y}_d$ will be negatively biased. Thus, $\hat{p}_d$ may be biased by some unknown amount. Likewise, $\hat{p}_d$ may be biased in the case that the domain and analysis variables do not employ the imputation of missing values.

In the 2016 detailed tables (CBHSQ, 2017f), *potential bias in the* $\hat{N}_d$, $\hat{Y}_d$, *or* $\hat{p}_d$ *estimates was not treated, although footnotes included on the tables provide detailed information about which estimates included or excluded missing values.* This problem may be illustrated by the following example, which corresponds to information presented in Tables 9.9A and 9.9B of the 2015 detailed tables.[25] Table 9.9A presents estimates of the past year use of several types of illicit drugs among people aged 12 to 17 for 2014 and 2015. These analysis variables are grouped into a two-level domain variable that is categorized according to whether a respondent had a past year major depressive episode (MDE). Table 12.1A of the 2015 detailed tables (CBHSQ, 2016d) shows the population estimate of people aged 12 to 17 as approximately 24,893,000. However, the subdomain population estimates summed to approximately 24,259,000, resulting in an estimate of $\hat{N}_m$ = 634,000 (approximately 2.5 percent of the total population). This number represents the estimated population not assigned to either domain. This negative bias can extend to various analysis variables, such as "Illicit Drugs." In 2015, the total estimate of people aged 12 to 17 who used illicit drugs in the past year was approximately 4,346,000. However, the 2015 estimates of people aged 12 to 17 who used illicit drugs in the past year among the valid subdomains (where past year MDE status was not missing) summed to 4,206,000, resulting in an estimate of $\hat{Y}_m$ = 140,000 (approximately 3.2 percent of the total population aged 12 to 17 who used illicit drugs in the past year).

Table 9.9B in the 2015 detailed tables (CBHSQ, 2016d) presents prevalence estimates of the past year use of several types of illicit drugs among people aged 12 to 17 for 2014 and 2015.

[25] Although this example references estimates from the 2015 detailed tables, similar examples can be found in the 2016 detailed tables.

Because $\hat{N}_m$ is positive and $\hat{Y}_m$ is positive for the "Illicit Drugs" analysis variable, the prevalence estimates for this variable may be biased by some unknown amount across the two domains. The 2015 prevalence estimates of illicit drug use reported in Table 9.9B for youths who had or did not have past year MDE are 31.5 and 15.3 percent, respectively. By recoding the item missingness of the domain variable MDE as having or not having MDE, the approximate range of possible bias values for each of these estimates is as follows: between -4.41 and 3.03 percent and between -0.35 and 0.55 percent, respectively.

As mentioned previously, some recoded variables classify unknown item responses in source variables as missing values, whereas others do not. That is, for some variables, item missingness is zero imputed (i.e., missing items are imputed as not having the condition or event of interest). Some examples of zero-imputed variables include various substance use treatment variables, select dependence and abuse variables (dependence and abuse variables for prescription drugs, inhalants, methamphetamine, and hallucinogens are imputed), and serious psychological distress variables.[26] Respondents with missing data that are not imputed are generally excluded from the relevant analyses. For the 2016 NSDUH, an investigation was completed to look at missing data rates in the 2016 detailed tables (CBHSQ, 2017f). The investigation was conducted only for new 2016 measures and existing measures where there was a break in trend starting with the 2016 NSDUH. For other measures, the results from the 2014 and 2015 investigations were assumed to still hold (CBHSQ, 2016e; 2017g). Rates of missingness were evaluated separately for each subpopulation within a table to allow for detection of variations in missingness rates among different subpopulations. Overall, it was concluded that missing data were not a concern for most topics presented in these tables. *However, items on perceived availability of various illicit drugs and source of prescription drugs obtained for most recent use in the detailed tables generally did have larger rates of missing data.* For example, the maximum weighted rate of missing data for the source of prescription drugs obtained for most recent use was 13.8 percent with about half of the subpopulations considered for these measures having a weighted missingness rate of greater than 5.0 percent in 2015.

For non-imputed recoded variables where unknown item responses were treated as negative responses and not as missing values, there is also potential bias. Assuming that unknown item responses are negative responses, a negative bias is created with magnitude dependent on the percentage of respondents with missing data and on the magnitude of the estimate. Specifically, higher levels of nonresponse paired with high estimates induce a larger negative bias. A lower level of nonresponse paired with lower prevalence estimates induces a smaller negative bias. Intermediate combinations induce a moderate negative bias.

The approximate range of bias can be illustrated with Table 5.16 of the 2015 detailed tables (2016d), which presents prevalence estimates of the past year receipt of substance use treatment among people aged 12 or older by various demographic characteristics for 2015.[27]

[26] This is not an exhaustive list of zero-imputed variables. For more information on specific variables, please see the 2016 public use data file codebook (CBHSQ/Substance Abuse and Mental Health Services Administration, 2017).

[27] Although this example references estimates from the 2015 detailed tables, similar examples can be found in the 2016 detailed tables.

Because the unknown responses for the analysis variable are treated as negative responses, the full population is used in the table (267,694,000, from Table 12.1A of the 2015 detailed tables) (CBHSQ, 2016d). Table 5.16A shows that 3,679,000 people aged 12 or older received substance use treatment in the past year for illicit drug or alcohol use (1.4 percent of the total population; Table 5.16B) in 2015. If unknown responses are excluded from the analysis, the estimated total population would be 264,778,000, resulting in a prevalence estimate of 1.4. (Note that there is a slight difference between the two prevalence estimates not seen because of rounding.) If, however, the unknown responses are treated as positive responses, then the estimated number of people aged 12 or older who received illicit drug treatment in the past year would be 6,595,000 (2.5 percent of the total population). Thus, there is an approximate range of bias based on the 2015 data between 0 and -1.1 percent.

4.2 Variance Estimation in the Presence of Missingness

SUDAAN® Software for Statistical Analysis of Correlated Data (RTI International, 2012) uses the number of strata (see Section 6 for more information) and number of primary sampling units (PSUs) in its variance calculations, even if there are some PSUs in which a variable is entirely missing for all sample members associated with that PSU. The rationale behind this approach is that there may be individuals in the target population who have nonmissing values in PSUs where no sample members have nonmissing values.

To illustrate how this is operationalized in SUDAAN, consider the following example. Suppose there is interest in calculating the mean of some variable (say, X), but there are missing values associated with variable X. SUDAAN then creates an internal subpopulation indicator variable (say, δ), where $\delta = 1$ if variable X is not missing, and $\delta = 0$ if variable X is missing. SUDAAN then internally calculates the mean and variance of variable X by using δX, assuming that the full sample mean is the same as the nonmissing sample mean.

For the variance estimator based on the Taylor series linearization approach, one of the terms in the variance estimator consists of the sum of squared deviations of PSU-level totals about their stratum-level means, divided by the number of PSUs in the stratum minus 1. Therefore, if SUDAAN encounters an incorrect number of PSUs within a stratum, then this term is incorrectly calculated. In addition, if there is only one PSU in a stratum, then the denominator for the variance term associated with that stratum becomes 0, and this causes the overall variance estimate to return an error message in SUDAAN. *By including all PSUs in a stratum, whether the PSU has reported values, SUDAAN computes the variances appropriately; that is, PSUs with nothing but missing values for a variable should never be excluded from an input file.*

5. Sampling Error

In sampling, statistics from different samples will vary and can differ from the true population parameter. Sampling error is the error caused by using statistics based on a sample instead of a complete census. Standard errors (SEs) are commonly used to measure how much these statistics differ from the true parameter. This measure is incorporated in common statistical methods such as significance testing (see Section 7) and confidence intervals (see Section 8). *As were the prevalence estimates, all of the variance estimates for prevalence (including those for prevalence based on annual averages from combined data) were calculated using a method in SUDAAN® Software for Statistical Analysis of Correlated Data (RTI International, 2012) that is unbiased for linear statistics.* This method is based on multistage clustered sample designs where the first-stage (primary) sampling units are drawn with replacement.

Because of the complex nature of the sampling design for the National Survey on Drug Use and Health (NSDUH) (specifically the use of stratified cluster sampling), key nesting variables were created for use in SUDAAN to capture explicit stratification and to identify clustering. Starting with the 2005 NSDUH,[28] a change was made in the way the key nesting variables were defined. Each state sampling region (SSR) appears in a different variance estimation stratum every quarter. This method has the effect of assigning the regions to strata in a pseudo-random fashion while ensuring that each stratum consists of four SSRs from four different states.

Two replicates per year are defined within each variance stratum (VEREP). Each variance replicate consists of four segments, one for each quarter of data collection. One replicate consists of those segments that are "phasing out" or will not be used in the next survey year. The other replicate consists of those segments that are "phasing in" or will be fielded again the following year, thus constituting the 50 percent overlap between survey years. A segment stays in the same VEREP for the 2 years it is in the sample. This simplifies computing SEs for estimates based on combined data from adjacent survey years.

Although the SEs of estimates of means and proportions can be calculated appropriately in SUDAAN using a Taylor series linearization approach, the actual SEs of estimates of totals may be smaller in situations where the domain size is poststratified to data from the U.S. Census Bureau. Because of the potential for gains in precision, alternatives for estimating SEs of totals were implemented in all of the 2016 detailed tables (Center for Behavioral Health Statistics and Quality [CBHSQ], 2017f), where appropriate.

Estimates of means or proportions, $\hat{p}_d$, such as drug use prevalence estimates for a domain *d*, can be expressed as a ratio estimate:

[28] The new design variables were created retroactively for 1999 through 2004; however, the old design variables continue to be used to generate 2002–2004 estimates in multiyear trend detailed tables and first findings reports (FFRs) for consistency with previously published estimates. Analyses beyond the detailed tables and FFRs typically use the new design variables for all available years.

$$\hat{p}_d = \frac{\hat{Y}_d}{\hat{N}_d},$$

where $\hat{Y}_d$ is a linear statistic estimating the number of substance users in the domain *d*, and $\hat{N}_d$ is a linear statistic estimating the total number of people in domain *d* (users and nonusers). The SUDAAN software package is used to calculate direct estimates of $\hat{Y}_d$ and $\hat{N}_d$ and can be used to estimate their respective SEs. A Taylor series approximation method implemented in SUDAAN provides estimates for $\hat{p}_d$ and its SE.

When the domain size, $\hat{N}_d$, is free of sampling error, an appropriate estimate of the SE for the total number of substance users is

$$\mathrm{SE}(\hat{Y}_d) = \hat{N}_d \mathrm{SE}(\hat{p}_d).$$

This approach is theoretically correct when the domain size estimates, $\hat{N}_d$, are among those forced to match their respective U.S. Census Bureau population estimates through the weight calibration process. In these cases, $\hat{N}_d$ is not subject to a sampling error induced by the NSDUH design. For more information on the person-level sampling weight calibration in the 2016 NSDUH, see CBHSQ (2018b).

For estimated domain totals, $\hat{Y}_d$, where $\hat{N}_d$ is not fixed (i.e., where domain size estimates are not forced to match the U.S. Census Bureau population estimates), this formulation still may provide a good approximation if it can be assumed that the sampling variation in $\hat{N}_d$ is negligible relative to the sampling variation in $\hat{p}_d$. This is a reasonable assumption for most estimates in this study.

For various subsets of estimates, the above approach yielded an underestimate of the variance of a total because $\hat{N}_d$ was subject to considerable variation. In 2000, an approach was implemented to reflect more accurately the effects of the weighting process on the variance of total estimates. This approach consisted of calculating SEs of totals for all estimates in a particular detailed table using the formula above when a majority of estimates in a table were among domains in which $\hat{N}_d$ was fixed during weighting or if it could be assumed that the sampling variation in $\hat{N}_d$ was negligible. Detailed tables in which the majority of estimates were among domains where $\hat{N}_d$ was subject to considerable variability were calculated directly in SUDAAN.

To improve on the accuracy of the SEs, a "mixed" method approach was implemented in which tables might include more than one method of SE estimation. This mixed approach was applied to selected tables in the 2004 NSDUH, and it was implemented across all tables starting with the 2005 NSDUH and continuing in subsequent years. *This approach assigns the method of*

SE calculation to domains within tables so that all estimates among a select set of domains with fixed $\hat{N}_d$ were calculated using the formula above, and all other estimates were calculated directly in SUDAAN, regardless of other estimates within the same table. The set of domains considered controlled (i.e., those with a fixed $\hat{N}_d$) was restricted to main effects and two-way interactions to maintain continuity between years. Domains consisting of three-way interactions may be controlled in one year but not necessarily in preceding or subsequent years. Using such SEs did not affect the SE estimates for the corresponding proportions presented in the same sets of tables because all SEs for means and proportions are calculated directly in SUDAAN. Appendix A contains SAS® (SAS Institute, 2017), SUDAAN, and Stata® (StataCorp, 2015) code examples that demonstrate how to compute SEs of proportions and both types of SEs of totals (controlled or uncontrolled; see Exhibits A.1 to A.6.

Table 5.1 contains a list of domains used in the 2016 detailed tables with a fixed $\hat{N}_d$ for the restricted-use data file.[29] This table includes the main effects and two-way interactions and can be used to identify the method of SE calculation employed for estimates of totals in the 2016 detailed tables (CBHSQ, 2017f). An example from the 2015 detailed tables would be Table 1.30, which presents estimates of illicit drug use among people aged 18 or older within the domains of gender, Hispanic or Latino (referred to as "Hispanic" hereafter) origin and race, education, and current employment. Estimates among the total population (age main effect), males and females (age by gender interaction), and Hispanics and non-Hispanics (age by Hispanic origin interaction) were treated as controlled in this table, and the formula above was used to calculate the SEs. The SEs for all other estimates, including white and black or African American (age by Hispanic origin by race interaction), were calculated directly from SUDAAN.[30] It is important to note that estimates presented in the detailed tables for racial groups are among non-Hispanics, unless noted otherwise. For instance, the domain for whites is actually non-Hispanic whites and is therefore a two-way interaction.

Some of the three-way interactions in Tables 1.28 to 1.87 of the 2015 detailed tables (CBHSQ, 2016d) were inadvertently treated as controlled domains. Specifically, some of the non-Hispanic white and non-Hispanic black estimates by age group were treated as controlled. As noted previously, the standard practice for the detailed tables is to always treat three-way interactions as uncontrolled because the ability to control for these precise domains during weight calibration can vary from year to year. These three-way interactions were treated as uncontrolled in Tables 1.29 to 1.66 of the 2016 detailed tables; therefore, the SEs of the total estimates for the non-Hispanic white and non-Hispanic black categories may differ from those in the 2015 detailed tables. Of the 60 affected 2015 detailed tables, 15 included 2014 and 2015 estimates and associated between-year significance testing. The remaining 45 detailed tables included 2015 estimates only. Corrected SEs for all the affected 2015 estimates are shown in the 2016 detailed tables, and an impact analysis determined there was a minimal impact on these SEs and significance testing. A few 2015 estimates are not shown in the 2016 detailed tables:

[29] See the variance estimation of totals section in the 2016 public use data file introduction for a list of domains with fixed $\hat{N}_d$ for the 2016 public use data file (CBHSQ/Substance Abuse and Mental Health Services Administration, 2017).

[30] Although this example references estimates from the 2015 detailed tables, similar examples can be found in the 2016 detailed tables.

estimates for 12- to 17-year-old respondents by combined gender, race, and Hispanic origin were found in Tables 1.29, 1.34, 1.39, 1.44, 1.49, 1.54, 1.59, 1.64, 1.69, 1.74, 1.79, and 1.84 of the 2015 detailed tables. Although these estimates are not found in the 2016 detailed tables, the SEs of the total estimates were correct in the 2015 detailed tables. Additionally, corrected SEs of the affected 2014 estimates and revised significance tests between the 2014 and 2015 estimates are not presented in the 2016 detailed tables.

Although not reported in the 2016 detailed tables, additional geographic interactions are also treated as domains with fixed $\hat{N}_d$ for other NSDUH analyses. Similar to geographic region, geographic division and individual states are considered controlled domains, and two-way interactions with state and gender, Hispanic origin, quarter, and age group (12 to 17, 18 to 25, and 26 or older), as well as the two-way interaction between geographic region and age group are all treated as domains with fixed $\hat{N}_d$. Additionally, quarter, although not used in the 2016 detailed tables, is considered a controlled domain with the two-way interaction with state being treated as a domain with fixed $\hat{N}_d$. Other two-way interactions with quarter such as gender or age group are not treated as controlled domains.

Table 5.1 Demographic and Geographic Domains in the Detailed Tables Forced to Match Their Respective U.S. Census Bureau Population Estimates through the Weight Calibration Process, 2016

Main Effects	Two-Way Interactions
Age Group	**Age Group × Gender**
12-17	(e.g., Males Aged 12 to 17)
18-25	
26-34	
35-49	**Age Group × Hispanic Origin**
50-64	(e.g., Hispanics or Latinos Aged 18 to 25)
65 or Older	
All Combinations of Groups Listed Above[1]	
Gender	**Age Group × Race**
Male	(e.g., Whites Aged 26 or Older)
Female	
Hispanic Origin	
Hispanic or Latino	**Age Group × Geographic Region**
Not Hispanic or Latino	(e.g., People Aged 12 to 25 in the Northeast)
Race[2]	
White	
Black or African American	**Gender × Hispanic Origin**
Others	(e.g., Not Hispanic or Latino Males)
Geographic Region	
Northeast	
Midwest	**Hispanic Origin × Race**
South	(e.g., Not Hispanic or Latino Whites)
West	

NOTE: Geographic division, state, and quarter are also controlled domains in the 2016 NSDUH. Geographic division, state, and quarter totals were forced to match their respective U.S. Census Bureau population estimates through the weight calibration process. Geographic division, state, and quarter were omitted from this table because geographic division, state, and quarter estimates are not shown in the 2016 NSDUH first findings reports and detailed tables.

[1] Combinations of the controlled age categories (12 or older, 18 or older, 26 or older, 35 or older, 50 or older, 18-49, 36-64, 50-65, etc.) can also be treated as controlled because the controlled groups will sum to the census totals for collapsed categories. Other combinations of age that include only partial sets of controlled groups (12-15, 18-30, etc.) should not be considered controlled.

[2] Unlike racial/ethnic groups discussed elsewhere in this report, race domains in this table include Hispanics in addition to individuals who were not Hispanic. In the poststratification adjustment, race had five categories in main effects: White, Black or African American, American Indian/Alaska Native, Asian, and Multiple Races. In two-way interactions of state by race, race had the same five categories as in the main effects. In other interactions, race had three categories: White, Black or African American, and Others. Note that some categories of race in the main effects or interactions may be collapsed in the final generalized exponential model because of model convergence issues.

Source: SAMHSA, Center for Behavioral Health Statistics and Quality, National Survey on Drug Use and Health, 2016.

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6. Degrees of Freedom

6.1 Background

To determine whether the observed difference between estimates is statistically significant, the degrees of freedom (*df*) are needed to locate the corresponding probability level (*p* value) of the test statistic. The test statistic is computed from the sample data and represents a numerical summary of the difference between the estimates under consideration; it is a random variable that has a predetermined distribution (such as Student's *t*, chi-square, or *F*). *The df characterize the amount of variation expected in the estimation of sampling error and are used in conjunction with the test statistic to determine probabilities and evaluate statistical significance.* In statistics, the number of *df* refers to the number of independent units of information in a sample relevant to the estimation of a parameter or calculation of a statistic. In general, the *df* of a parameter estimate are equal to the number of independent observations that go into the estimate minus the number of other parameters that need to be estimated as an intermediate step. The *df* are also used to compute the confidence intervals (CIs) discussed in Section 8. The upper and lower limits of the CIs are defined by a constant value that is chosen to yield a level of confidence based on the *df*.

In practice, beyond a certain value, which *df* value is used has little impact. For example, the 97.5th percentile of the *t*-distribution is used in the National Survey on Drug Use and Health (NSDUH) to create 95 percent CIs and for two-sided hypothesis tests, and this does not change much once there are about 50 *df*. Thus, results with 50 *df* are similar to results with the 900 *df* used for the 2002–2013 NSDUHs and the 750 *df* used for the 2014–2016 NSDUHs (Figure 6.1). In addition, Table 6.1 shows the large sample 95 percent CI for a "typical" estimate—for example, the percentage of past month users of alcohol in 2015—for different *df*. The CIs are similar.[31]

The *df* for NSDUH vary based on the sample design. Table 6.2 shows the *df* for specific states per the NSDUH sample designs.[32] Starting with the 2005 NSDUH, a change in the definition of the variance estimation strata had the effect of increasing the number of *df* for the state-level estimates fourfold while preserving the number of *df* for the national estimates. Revised design variables were created retroactively for years before 2005 (see footnote 28). *When producing 2002–2013 NSDUH estimates at the national level, there are 900 df.* If an analysis involves individual states, the *df* are determined by the number of strata in which the state is included. In the 2002–2013 surveys, there were two sample size groups. Large sample states (i.e., California, Florida, Illinois, Michigan, New York, Ohio, Pennsylvania, and Texas)

[31] Although this example references estimates from the 2015 detailed tables, similar examples can be found in the 2016 detailed tables.

[32] Users of the 2016 public use file (Center for Behavioral Health Statistics and Quality [CBHSQ]/Substance Abuse and Mental Health Services Administration [SAMHSA], 2017) may find inconsistencies with the specific *df* presented in this report because the specific information referenced is based on the restricted-use dataset that was used to create the 2016 detailed tables (CBHSQ, 2017f) and the 2016 first findings reports (FFRs) (CBHSQ, 2017c; Lipari et al., 2017; Park-Lee et al., 2017).

have 192 *df* because each large state is in 192 strata. Small sample states (i.e., all other states including the District of Columbia) have 48 *df* because each small state is in 48 different strata.

Figure 6.1 97.5th Percentiles of *t*-Distributions for Varying Degrees of Freedom

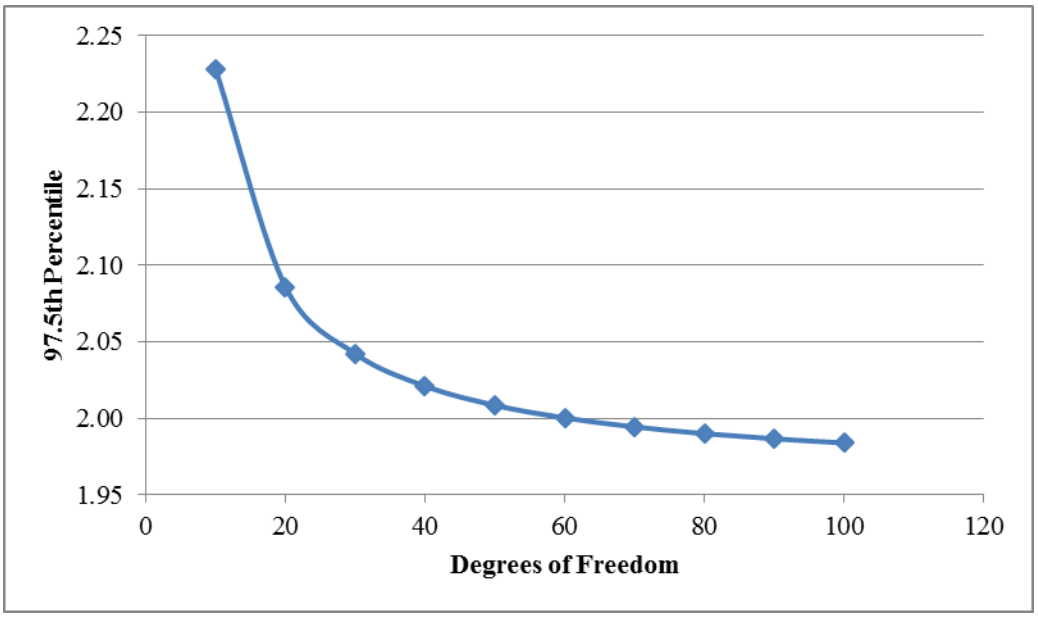

Table 6.1 Ninety-Five Percent Confidence Intervals for the Percentage of Past Month Users of Alcohol, Using Different Degrees of Freedom, 2015

Degrees of Freedom	Critical Value of the *t*-Distribution	95% Confidence Interval	
		Lower Limit	Upper Limit
10	2.2281	50.96	52.38
20	2.0860	51.01	52.34
30	2.0423	51.02	52.32
40	2.0211	51.03	52.31
50	2.0086	51.03	52.31
60	2.0003	51.03	52.31
70	1.9944	51.04	52.31
80	1.9901	51.04	52.30
90	1.9867	51.04	52.30
100	1.9840	51.04	52.30
500	1.9647	51.05	52.30
750	1.9631	51.05	52.30
900	1.9626	51.05	52.30
1,800	1.9613	51.05	52.30

NOTE: The percentage of past month users of alcohol used to produce the data in this table is 51.67 percent, with a corresponding standard error of 0.32, both rounded to 2 decimal places.

Source: SAMHSA, Center for Behavioral Health Statistics and Quality, National Survey on Drug Use and Health, 2015.

Table 6.2 Degrees of Freedom for Specific States per the NSDUH Sample Design Based on the Restricted-Use Dataset

States	Sample Design Years[1]	Degrees of Freedom[2]
California	2014–2016	144
	2005–2013	192
	2002–2004	192
Florida, New York, and Texas	2014–2016	120
	2005–2013	192
	2002–2004	192
Illinois, Michigan, Ohio, and Pennsylvania	2014–2016	96
	2005–2013	192
	2002–2004	192
Georgia, New Jersey, North Carolina, and Virginia	2014–2016	60
	2005–2013	48
	2002–2004	48
Remaining 38 states and the District of Columbia	2014–2016	48
	2005–2013	48
	2002–2004	48

[1] The NSDUH sample design variables were revised in 2005 and 2014. The 2005 revisions were applied retroactively to the 1999 through 2004 NSDUHs. Because of survey improvements in the 2002 NSDUH, the 2002 data constitute a new baseline, so this table does not include information before 2002.

[2] The degrees of freedom in this table are based on the new sample design variables. If using the old sample design variables for NSDUH years 2002–2004, the state degrees of freedom listed in this table would be divided by 4.

Source: SAMHSA, Center for Behavioral Health Statistics and Quality, National Survey on Drug Use and Health, 2002–2016.

Changes were made to the 2014 through 2017 sample allocation in order to increase the sample in the original 43 small states to improve precision of the state and substate estimates while moving closer to a proportional allocation in the larger states. This design change moved the sample from two state sample size groups (large and small) to five state sample size groups. In the revised design, sampling strata called state sampling regions (SSRs) were formed within each state. *The partitioning divided the United States into a total of 750 SSRs, which results in 750 df for national estimates.* States in sample size group 1 (i.e., California) have 144 *df*, states in sample size group 2 (i.e., Florida, New York, and Texas) have 120 *df*, states in sample size group 3 (i.e., Illinois, Michigan, Ohio, and Pennsylvania) have 96 *df*, states in sample size group 4 (i.e., Georgia, New Jersey, North Carolina, and Virginia) have 60 *df*, and states in sample size group 5 (i.e., the remaining 38 states and the District of Columbia) have 48 *df*.

Appendix A contains examples that demonstrate how to define the *df* within SUDAAN® Software for Statistical Analysis of Correlated Data (RTI International, 2012) or Stata® (StataCorp, 2015) to compute design-based estimates.

Under the NSDUH sample designs, for an analysis of a group of states, the *df* would be less than or equal to the sum of the *df* for each individual state due to overlap of strata.

Therefore, the specific number of df should be computed by counting the unique values of VESTR (variance estimation [pseudo] stratum) for the particular geographic area of interest. For these types of specific state analyses (or other subpopulations of interest), the *df* can be calculated outside of SUDAAN and this value entered manually into SUDAAN for use in testing; otherwise, the *df* are computed using the entire dataset. Similar methods can be used to compute appropriate *df* for any geographic region comprising counties. Using this technique with the public use file will give similar, but not always exact, results.

The technique of counting the number of unique values of VESTR (see above) can also be used to compute the number of *df* for analyses based on combining survey data across years. *An alternative technique for computing the df for analyses that use data combined (or pooled) across NSDUH sample design years involves summing the df from each sample design year (see Table 6.2) to determine the df for the NSDUH years and states of interest) because each sample design (i.e., 2002–2004, 2005–2013, 2014–2017) contains unique variance strata.* For example, when pooling 2013 and 2014 NSDUH data, the *df* for California would be 192 (2013) + 144 (2014) = 336 because the years being pooled come from two different sample designs. However, if pooling 2012 and 2013 NSDUH data, which both come from the same sample design, the *df* would simply be 192. Pooled data examples can be found in Exhibits A.1 through A.3 showing how the *df* can be designated.

6.2 Degrees of Freedom Used in Key NSDUH Analyses

The current practices for applying *df* to NSDUH data depends on the type of analyses. Table 6.3 summarizes key types of NSDUH analyses and the *df* used for these analyses for the various survey design years. *The detailed tables and FFRs use the national df for the most current survey year (including census region and division and estimates for all years including pooled years), with the exception of the mean age of first use (AFU) and the average number of days estimates.* The current year *df* is used because when conducting significance testing between estimates with different *df* (e.g., 2014 vs. 2013), the lower *df* provide a more conservative test and are used. For all of the currently analyzed years of NSDUH data, the current year's *df* have always been less than or equal to the previous years' *df*.

AFU and average number of days used estimates are treated differently because of the possibility of smaller sample sizes (i.e., the sample sizes for AFU estimates are typically the number of past year initiates); therefore, they belong to fewer variance estimation strata. Based on the NSDUH suppression rules, the sample size threshold for suppression of an average estimate is 10, whereas for prevalence estimates, it is 100. Thus, it is possible for nonsuppressed average estimates to have smaller sample sizes than prevalence estimates. For example, the subpopulation for estimates of mean AFU includes only past year initiates of prescription drugs and lifetime users of other drugs, which could be small for drugs with low prevalence estimates of use. An impact assessment was done using 2012–2013 data to determine whether the results of statistical comparisons between the means for the 2 years would be affected if the *df* were changed from the national *df* (900 in 2013) to the number of nonempty strata (the number of strata containing respondents with valid data to each specific question within the subpopulation). This latter value would produce more conservative tests. *After the impact assessment, a decision was made to use the number of nonempty strata as the df for the detailed tables that include*

estimates of mean AFU. This decision was expanded to include estimates for all average estimates in 2016.

Unlike the detailed tables and the FFRs, which use the national *df* for estimates by geographic subgroups (census region and division), special analyses and methodological reports follow the procedures described in Section 6.1 for these subgroups. The *df* used for key NSDUH analyses are summarized in Table 6.3. *For NSDUH analyses that compare two subpopulations (including those that compare subpopulations with the full population), standard practice is to use the smaller of the two values for df to err on the side of being conservative.* For analyses where the subpopulation is not geographic in nature (e.g., members of a certain race or age category, past year users of a certain drug), standard practice is to use the same *df* value that is used for analyses involving the whole population.

Table 6.3 Key NSDUH Analyses and Degrees of Freedom for the Restricted-Use Data File and the Public Use Data File, by Sample Design Years, 2002–2016

Analyses	Sample Design Years[1]	Degrees of Freedom for Restricted-Use (Public Use) Data File[2]
Special analyses involving the whole population or a nongeographic subpopulation[3]	2014–2016	750 (50)
	2005–2013	900 (60)
	2002–2004	900 (60)
Special analyses involving a single state	See Table 6.2.	See Table 6.2.
Special analyses involving other geographic subpopulations[3]	Any	Count of the unique values of VESTR (variance estimation [pseudo] stratum) for the particular geographic area of interest[4]
Detailed tables (including mental health in years before 2015) or first findings reports (FFRs) with estimates of mean age at first use	2014–2016	Number of nonempty[5] strata (for each estimate/subpopulation)
	2005–2013	900 (60)
	2002–2004	900 (60)
All other detailed tables (including mental health in years before 2015) and FFRs (including geographic subpopulations)	2014–2016	750 (50)
	2005–2013	900 (60)
	2002–2004	900 (60)

[1] The NSDUH sample design variables were revised in 2005 and 2014. The 2005 revisions were applied retroactively to the 1999 through 2004 NSDUHs. Because of survey improvements in the 2002 NSDUH, the 2002 data constitute a new baseline, so this table does not include information before 2002.

[2] The degrees of freedom shown first in this column are based on the restricted-use data files, and the degrees of freedom in parentheses are based on the public use data file. State is not available on the public use data file; thus, only information on the degrees of freedom based on the restricted-use data files is provided.

[3] Some analyses capped the degrees of freedom at 900, regardless of year combinations across the study year groups. This rule is not consistently applied to all special analyses and reports.

[4] Users of the 2016 public use file (CBHSQ/SAMHSA, 2017) may find inconsistencies in the counts when comparing them with published data.

[5] A stratum or primary sampling unit (PSU) is *empty* for a given subpopulation if the respondent pool contains no subpopulation members in the stratum or PSU.

Source: SAMHSA, Center for Behavioral Health Statistics and Quality, National Survey on Drug Use and Health, 2002–2016.

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7. Statistical Significance of Differences

Once the degrees of freedom (*df*) have been determined, various methods used to compare prevalence estimates may be employed. This section describes the impact on significant testing from the 2014 sample redesign, the 2015 questionnaire redesign, and the 2016 questionnaire changes as well as the methods used to compare prevalence estimates, examples showing how to compute the comparison of estimates between years, and the impact of rounding in interpreting testing results.

Customarily, the observed difference between estimates is evaluated in terms of its statistical significance. Statistical significance is based on the size of the test statistic and its corresponding *p* value, which refers to the probability that a difference as large as that observed would occur because of random variability in the sample estimates if there were no differences in the population prevalence values being compared. The significance of observed differences is generally reported at the .05 and .01 levels when the *p* value is defined as less than or equal to the designated significance level.

Significance tests were conducted on differences between prevalence estimates from the 2016 National Survey on Drug Use and Health (NSDUH) and previous years of NSDUH back to 2002. *Because of survey design changes implemented in 2002, data from the 2002 NSDUH and onward should not be compared with data from survey years before 2002. Additionally, questionnaire changes in 2015 and 2016 caused many estimates to break trend. In the case of 2016 questionnaire changes, 2016 estimates should not be compared with prior-year estimates (see Section 2.2 for more information). In the case of 2015 questionnaire changes, 2016 estimates should not be compared with estimates before 2015 (see Section 2.3 for more information)*. In some years, significance tests are also conducted on differences between prevalence estimates from combined years of survey data (e.g., 2012–2013 vs. 2014–2015); however, the 2016 detailed tables (Center for Behavioral Health Statistics and Quality [CBHSQ], 2017f) did not show any combined year estimates. Within-year tests were conducted on differences between prevalence estimates for various populations (or subgroups) of interest using data from the 2016 survey. In addition to comparing subpopulations, linear trend tests for all data points across all years of interest were performed. Tests against the national average were also conducted, comparing individual subgroups with the full population for certain demographics such as region and division.

7.1 Impact of 2014 Sample Redesign on Significance Testing between Years

The 2014–2017 NSDUH sample was redesigned and may continue to be used for future years. The primary purpose of the redesign was to redistribute the sample sizes by state and by age group, so the sample size in each state was more proportional to the state population, and similarly for age groups (i.e., youths aged 12 to 17 and young adults aged 18 to 25 were oversampled less, and older adults aged 50 or older were undersampled less). *The change in sample design with regard to states resulted in greater precision (i.e., smaller standard errors [SEs]) overall, and the change in sample design with regard to age groups resulted in slightly decreased precision for youths and young adults, but increased precision for older adults; the*

increase in precision for older adults was much larger than the decrease in precision for youths and younger adults.

Other sample design changes in 2014 included the following: the use of the 2010 census data (instead of projections from the 2000 census), the 2006 to 2010 American Community Surveys, and Nielsen Claritas to provide more up-to-date information for constructing the sampling frame and thereby slightly increasing precision; reducing the number of state sampling regions so that national, regional, and state *df* were typically reduced (e.g., from 900 in 2013 and earlier to 750 in 2014 for national estimates), but the effect on critical values of the *t*-distribution was small (i.e., relative changes all less than 1 percent); the average cluster (i.e., segment) size was increased while simultaneously reducing the number of clusters, which did not result in a significant loss of precision.

Changes (mainly increases) in the precision of estimates due to the 2014 sample redesign are likely to affect significance testing. For example, suppose an estimate in 2013 is identical to that in 2014, but the 2014 estimate is more precise; it is then possible that a test between 2013 and 2012 estimates may not be significant, but the same test between 2014 and 2012 estimates may be significant because the 2014 estimate has a smaller SE.

7.2 Impact of 2015 Questionnaire Redesign on Significance Testing between Years

In 2015, the NSDUH questionnaire underwent a partial redesign to improve the quality of the NSDUH data and to address the changing needs of policymakers and researchers with regard to substance use and mental health issues. For several measures, these changes led to actual or potential breaks in the comparability of data in 2015 with corresponding data from prior years. *Where this occurred, prior-year estimates in the 2015 detailed tables (CBHSQ, 2016d) were not comparable (replaced with the symbol "nc") or not reported (replaced with the symbol "nr"), and significance testing between years was not conducted*. See Section 2.2 for a list of measures with a trend break and for more details about the various questionnaire changes.

7.3 Impact of 2016 Questionnaire Changes on Significance Testing between Years

In 2016, several questionnaire changes helped to improve data quality. For driving under the influence (DUI) measures, the changes led to a break in comparability of data in 2016 with corresponding data from prior years. In the 2016 detailed tables (CBHSQ, 2017f), prior-year DUI estimates were not comparable (replaced with the symbol "nc") or not available (replaced with the symbol "--"), and significance testing between years was not conducted. See Section 2.3 for more details on the changes.

7.4 Comparing Prevalence Estimates between Years

When comparing prevalence estimates, one can test the null hypothesis (no difference in the population) against the alternative hypothesis (there is a difference in the population) using the standard *t* test (with the appropriate *df*) for the difference in proportions test, expressed as

$$t_{df} = \frac{\hat{p}_1 - \hat{p}_2}{\sqrt{\text{var}(\hat{p}_1) + \text{var}(\hat{p}_2) - 2\text{cov}(\hat{p}_1, \hat{p}_2)}}, \quad (1)$$

or

$$t_{df} = \frac{\hat{p}_1 - \hat{p}_2}{\sqrt{\text{var}(\hat{p}_1) + \text{var}(\hat{p}_2) - 2\rho(\hat{p}_1, \hat{p}_2)\text{SE}(\hat{p}_1)\text{SE}(\hat{p}_2)}}, \quad (2)$$

where in both formulas, *df* = the appropriate degrees of freedom, $\hat{p}_1$ = the first prevalence estimate, $\hat{p}_2$ = the second prevalence estimate, $\text{var}(\hat{p}_1)$ = the variance of the first prevalence estimate, and $\text{var}(\hat{p}_2)$ = the variance of the second prevalence estimate. In the first formula, $\text{cov}(\hat{p}_1, \hat{p}_2)$ = covariance between $\hat{p}_1$ and $\hat{p}_2$. In the second formula, the covariance between $\hat{p}_1$ and $\hat{p}_2$ is displayed as the product of the correlation between $\hat{p}_1$ and $\hat{p}_2$ and the SEs of $\hat{p}_1$ and $\hat{p}_2$, where $\rho(\hat{p}_1, \hat{p}_2)$ = the correlation between $\hat{p}_1$ and $\hat{p}_2$ and $\text{SE}(\hat{p}_1)\text{SE}(\hat{p}_2)$ = the product of the SEs for $\hat{p}_1$ and $\hat{p}_2$ (i.e., the two formulas are equivalent; the first formula is defined in terms of the covariance, and the second is defined in terms of the correlations and SEs). Generally, the correlations between estimates in adjacent years are very small and positive; thus, ignoring the correlation in the second formula will usually result in a slightly more conservative test outcome, which is a test that is less likely to reject the null hypothesis that there is no difference in the two estimates. However, a negative correlation is possible and would result in a liberal test, which means it would be more likely to reject the null hypothesis that there is no difference in the two estimates. Additionally, the second (simplified) formula can be used in the case of two independent (i.e., uncorrelated) samples, like in the case of comparing two nonadjacent year estimates. Note that the first and second prevalence estimates may take the form of prevalence estimates from two different survey years (e.g., 2015 and 2016, respectively), prevalence estimates from sets of combined survey data (e.g., 2013–2014 annual averages and 2015–2016 annual averages, respectively), or prevalence estimates for different populations of interest within a single survey year. Quick tests (where the correlation of 0 is assumed) are great tools for gaining a better understanding of published estimates; however, the results of these quick tests should be confirmed using NSDUH data and appropriate software.

Under the null hypothesis, the test statistic *t* is a random variable that asymptotically follows a *t*-distribution. Therefore, calculated values of *t*, along with the appropriate *df*, can be used to determine the corresponding probability level (i.e., *p* value). *Whether testing for differences between years or from different populations within the same year, the covariance term in the formula for t (see formula 1 above) will, in general, not be equal to 0.* SUDAAN® Software for Statistical Analysis of Correlated Data is used to compute estimates of *t* along with the associated *p* values such that the covariance term is calculated by taking the sample design into account (RTI International, 2012). A similar procedure and formula for *t* are used for estimated totals; however, it should be noted that because it was necessary to calculate the SE indirectly outside of SUDAAN using the mean that was computed using SUDAAN for domains forced by the weighting process to match their respective U.S. Census Bureau population estimates, the corresponding test statistics also were computed indirectly outside of SUDAAN.

SUDAAN along with auxiliary SAS® code (SAS Institute, 2017) and Stata® (StataCorp, 2015) examples showing the computational methods for generating *p* values of estimates of *t* and estimated totals can be found in Appendix A (Exhibits A.10 through A.21).

Under the null hypothesis, the test statistic with known variances asymptotically follows a standard normal (*Z*) distribution. However, because the variances of the test statistic are estimated, its distribution is more accurately described by the *t*-distribution for finite sample sizes. A sufficiently large sample size is required for the asymptotic properties to take effect, and this is usually determined through the suppression criteria applied to the estimates (see Section 10). As the *df* approach infinity, the *t*-distribution approaches the *Z* distribution. *That is, because most of the statistical tests performed have 750 df (see Section 6), the t tests performed produce approximately the same numerical results as if a Z test had been performed.*

If SUDAAN is not available to compute the standard t test, using published estimates can provide similar pairwise testing results. When comparing prevalence estimates shown in the detailed tables with their SEs, independent *t* tests for the difference of proportions can be performed and usually will provide the same results as tests performed in SUDAAN (see Sections 7.5 and 7.6). However, where the *p* value is close to the predetermined level of significance, results may differ for two reasons: (1) the covariance term is included in the SUDAAN tests, whereas it is not included in independent *t* tests, and (2) the reduced number of significant digits shown in the published estimates may cause rounding errors in the independent *t* tests.

7.5 Example of Comparing Prevalence Estimates between Years

The following example reproduces the difference in the proportions tested between 2014 and 2015 for a measure shown in Table 2.1B of the 2015 detailed tables (CBHSQ, 2016d).[33] Table 2.1B displays the prevalence for lifetime, past year, and past month tobacco and alcohol use. This example will test the difference between 2014 and 2015 past month tobacco product use. Past month tobacco product use shown in Table 2.1B has a prevalence estimate of 25.2 percent in 2014 and 23.9 percent in 2015. The corresponding SEs shown in Table 2.1D are 0.28 percent for 2014 and 0.26 percent for 2015. Assuming that the source data are not available and/or the user does not have access to appropriate software (i.e., SUDAAN), the second *t* test formula provided earlier in this section can be used with the assumption that the correlation is 0.

Note that

$$\text{var}(\hat{p}_i) = (\text{SE}(\hat{p}_i))^2,$$

$$t_{750} = \frac{25.2 - 23.9}{\sqrt{0.28^2 + 0.26^2 - 2(0)(0.28)(0.26)}} = 3.4023.$$

Using a *t* test to find the corresponding *p* value when $t = 3.4023$ and $df = 750$ results in *p* value = 0.0007. This is very close to the SUDAAN-calculated *p* value of 0.0002 provided in

[33] Although this example references estimates from the 2015 detailed tables, similar examples can be found in the 2016 detailed tables.

Table 2.1P. This example confirms that the difference between the 2014 estimate of 25.2 percent and the 2015 estimate of 23.9 percent is statistically significant at the 0.01 level as indicated by footnote b included on the 2014 estimate in Table 2.1B. Note that the calculated *p* value assuming the correlation is 0 is larger than the actual *p* value, which supports the earlier assertion that assuming the correlation is 0 results in a more conservative *p* value. Note, however, that this calculation could produce a smaller *p* value due to the use of rounded estimates from the table. (If the unrounded estimates had been available, the formula would yield a slightly larger *p* value than what is published in the tables.)

Following is an example using the same formula with the unrounded estimates and the covariance from SUDAAN. The extra digits and the covariance change the *t*-score slightly, resulting in the published *p* value of 0.0002. Note that the *t* statistic from the below formula gives the same results as the test in SUDAAN.

$$t_{750} = \frac{25.23322447 - 23.89257397}{\sqrt{(0.27760137)^2 + (0.2610112)^2 - 2(0.0889702487627662)\,(0.27760137)(0.2610112)}} = 3.6859$$

Also note that the correlations between estimates in adjacent years are generally very small and positive, but a negative correlation is possible. Estimates with negative correlations will also be close to 0; thus, the differences in SUDAAN-calculated *p* values and *p* values calculated from published estimates using the second *t* test formula provided earlier in this section (where the correlation is assumed to be 0) would still be minimal, such as the small differences shown in this section. *However, where the p value is close to the predetermined level of significance, results may differ.*

7.6 Example of Comparing Prevalence Estimates between Years in Excel

Using the same numbers presented in Section 7.5, this example uses Excel functions to produce the same *p* value produced in the previous example. The same assumption is made about the correlation (i.e., it is 0) and that $\text{var}(\hat{p}_i) = (\text{SE}(\hat{p}_i))^2$. The correlation of 0 results in the simplified formula shown below (additionally, the variances have been replaced by SEs squared).

$$t_{df} = \frac{\hat{p}_1 - \hat{p}_2}{\sqrt{(\text{SE}(\hat{p}_1))^2 + (\text{SE}(\hat{p}_2))^2}}$$

Excel can be used to set up a simple table (shown below) to compare prevalence estimates. Cells A2 through E2 are the known values input by the user. Cells F2 and G2 contain functions. This table could extend over several rows to aid in comparing many different pairs of prevalence estimates (i.e., data for columns A through E would have to be entered for each row, and then the formulas in columns F and G could be copied for all rows).

	A	B	C	D	E	F	G
1	p_1	p_2	SE(p_1)	SE(p_2)	*df*	*t*	*p* value
2	25.2	23.9	0.28	0.26	750	3.4023	0.0007

The standardized test statistic is found using the simplified formula for t_{df}.

	A	B	C	D	E	F	G
1	p_1	p_2	SE(p_1)	SE(p_2)	*df*	*t*	*p* value
2	25.2	23.9	0.28	0.26	750	=(A2-B2)/SQRT(C2^2+D2^2)	0.0007

The Excel T.DIST.2T function then calculates the two-tailed Student's *T*-Distribution, a continuous probability distribution.

	A	B	C	D	E	F	G
1	p_1	p_2	SE(p_1)	SE(p_2)	*df*	*t*	*p* value
2	25.2	23.9	0.28	0.26	750	3.4023	=T.DIST.2T(ABS(F2),E2)

Alternatively, the Excel NORM.S.DIST function can be used to calculate the Standard Normal Cumulative Distribution Function because the *t*-distribution approaches the *Z* distribution as the *df* approach infinity. Tests performed having 750 *df* produce approximately the same numerical results as if a *Z* test had been performed. Note that this function refers to the test statistic as *Z* and does not require the *df* input.

	A	B	C	D	E	F	G
1	p_1	p_2	SE(p_1)	SE(p_2)	*df*	*Z*	*p* value
2	25.2	23.9	0.28	0.26	750	3.4023	=2*(1-NORMSDIST(ABS(F2)))

The T.DIST.2T and NORM.S.DIST functions yield the same *p* value, 0.0007. Although not generated in all NSDUH publications, some publications do include sampling error in the form of 95 percent confidence intervals (CIs). In terms of testing for differences between prevalence estimates shown with 95 percent CIs, it is important to note that two overlapping 95 percent CIs do not imply that their estimates are statistically equivalent at the 5 percent level of significance. For additional information, see Schenker and Gentleman (2001) and Payton, Greenstone, and Schenker (2003).

7.7 Comparing Prevalence Estimates in Categorical Subgroups

In addition to examining estimates between years, significance testing is also used when comparing population subgroups defined by three or more levels of a categorical variable within a given year. In this type of situation, log-linear chi-square tests of independence of the subgroup and the prevalence variables were conducted first to control the error level for multiple comparisons. Although these tests are generally not published in the detailed tables, they can aid in report writing for NSDUH publications to verify statements implying significance such as claiming that the prevalence for a measure of interest varies by age groups. In Appendix A, see Exhibit A.30 for example SUDAAN code and Exhibit A.31 for example Stata code showing this type of testing. *If Shah's Wald F test (transformed from the standard Wald chi-square) indicated overall significant differences, the significance of each particular pairwise comparison of interest was tested using SUDAAN analytic procedures to properly account for the sample design (RTI International, 2012).* Individual pairwise tests are also used in report writing for

NSDUH publications to verify statements implying significance such as claiming that a particular age group has the highest prevalence for a measure of interest.

Significance testing can also compare individual subgroups with the full population (e.g., adults employed full-time vs. all adults). Because this testing involves two overlapping domains, a stacked dataset that includes two records for each respondent in the overlap is needed for analysis. This type of testing was added for demographics (race/Hispanicity and region) commonly compared in the 2016 detailed tables (CBHSQ, 2017f). Tests against the national average are generally not published in the detailed tables, but they can aid in report writing for NSDUH publications to verify statements implying significance such as claiming that the prevalence for a measure of interest is higher or lower among a certain region when compared with the national average. In Appendix A, see Exhibit A.28 for example SUDAAN code and Exhibit A.29 for Stata code showing this type of testing.

7.8 Comparing Prevalence Estimates to Identify Linear Trends

In addition to comparing subpopulations or one year versus another year, it can also be useful to test the linear trend for all data points, across all years of interest. *Linear trend testing can inform users about whether prevalence use has decreased, increased, or remained steady over the entire span of the years of interest or about changes in specific measures.* Various methods can be used to test linear trend. Linear trend testing is produced for the detailed tables as applicable, but it is only used to aid in NSDUH report writing and is not published. These linear trend tests are implemented using the SUDAAN procedure DESCRIPT with CONTRAST statements looking across years to evaluate change over time. In Appendix A, see Exhibit A.34 for example SUDAAN code and Exhibit A.35 for example Stata code showing this type of linear trend testing.

For linear testing within the detailed tables, the DESCRIPT procedure is used in the mass production of detailed tables *only* to aid in report writing regarding whether a particular measure has remained stable, increased, or decreased over time. This method uses the *t* test, similar to the pairwise method used when testing means between years and between demographic levels within the detailed tables. Instead of using PAIRWISE statements, type I errors (incorrectly producing significant differences) are controlled by using orthogonal polynomial coefficients in the CONTRAST statement. Although pairwise testing gives detailed information for testing between 2 years, it does not perform as well for overall trend information and increases type I errors.

The DESCRIPT procedure for linear testing within the detailed tables is a good approximation to a model-based approach. The 2014 redesign impact assessment report (RIAR) (CBHSQ, 2015e) and the 2015 RIAR (CBHSQ, 2017e) also include linear trend testing and implemented the testing using a model-based approach, specifically linear regression, logistic regression, and multinomial logistic regression models to determine whether there were breaks in trends for the most current year. Models were also run and stratified by age and state group. The more complex model-based approach was used to incorporate more information about the outcome into the models (i.e., what type of data are being modeled) and to allow for multiple covariates, which helped determine whether there was a break in trend. This model-based approach was specific to the RIARs, of which the 2015 RIAR will be featured as part of the 2015

Methodological Resource Book. In Appendix A, see Exhibit A.36 for example SUDAAN code and Exhibit A.37 for example Stata code showing the model-based linear trend testing.

The model-based method used in the RIARs is more flexible to measure a change in measurement over time when controlling for multiple covariates as needed. The modeling method can be used to estimate more specific measures, such as testing a year effect in a trend model that adjusts for seasonal effects and redesign effects, or comparing an estimate with an estimated forecast using data up to a specified year. The modeling method may yield a slightly different result than the DESCRIPT method under similar settings. Because the purpose of the testing for the detailed tables is to test whether any observed difference across years is significant without consideration of other covariates, the DESCRIPT method was used for its simplicity to be incorporated into the table generation software under the given time constraints.

7.9 Impact of Rounding in Interpreting Testing Results

Prevalence estimates in the form of percentages are presented in the detailed tables and first findings reports and are rounded to the nearest tenth of a percent. *Testing between two rounded prevalence estimates can indicate significant or nonsignificant differences involving seemingly identical estimates.* Examples below using data from the 2015 detailed tables are provided as follows to aid users in interpreting significance testing results:[34]

1. Differences between the estimate in a given year (e.g., 2014) and the estimate in the current year (e.g., 2015) are shown as statistically significant, but the percentages appear to be identical. For example, in Table 1.18B of the 2015 detailed tables (CBHSQ, 2016d), the estimate for lifetime crack use among youths aged 12 to 17 was 0.1 percent for 2014 and 2015 and was indicated as significantly different. Although the rounded estimates appear the same, the unrounded estimates were 0.1390 percent for 2014 and 0.0501 percent for 2015.
2. Difference between the estimate in prior year A (e.g., 2002) and the estimate in the current year (e.g., 2015) is statistically significant, but the difference between the estimate in prior year B (e.g., 2004) and the estimate in the current year (e.g., 2015) is not significant, but the estimates for prior years A and B appear to be identical. For example, in Table 7.3B of the 2015 detailed tables (CBHSQ, 2016d), the estimate for past month crack use among people aged 12 or older is 0.2 percent for 2002, 2004, 2007, 2009, and 2012, but only the 2002 and 2007 estimates are significantly different from the 2015 estimate of 0.1 percent. Although the rounded estimates for 2002, 2004, 2007, 2009, and 2012 appear the same, the unrounded estimates were 0.2411 for 2002, 0.1940 for 2004, 0.2464 percent for 2007, 0.1973 percent for 2009, and 0.1705 percent for 2012.

[34] Although this example references estimates from the 2015 detailed tables, similar examples can be found in the 2016 detailed tables.

8. Confidence Intervals

In some National Survey on Drug Use and Health (NSDUH) publications, sampling error has been quantified using 95 percent confidence intervals (CIs). CIs provide a scale to judge how close the sample statistic is likely to be to the true population parameter under repeated sampling. A 95 percent CI, which varies for each sample, is expected to capture the true population parameter in 95 percent of samples. The interval provides a value above and below the estimate and is determined by using the sampling distribution and standard error. The sampling distribution translates the confidence level into the appropriate multiplier, and the standard error measures how much statistics differ from the parameter because of sampling variability. Samples with more variability will result in a larger spread in the CI. *Symmetric CIs for small proportions may lead to the undesirable result of a lower CI limit that is less than 0.* Frequently, NSDUH estimates are small percentages (i.e., are close to 0), and in that case, a logit transformation of the estimate provides favorable properties. For example, the logit transformation yields asymmetric interval boundaries between 0 and 1 that are more balanced with respect to the true probability that the true value falls below or above the interval boundaries. This is partly because for values close to 0, the distribution of a logit-transformed estimate approximates the normal distribution more closely than the standard estimate.

To illustrate the logit transformation method, let the proportion P_d represent the true proportion for a particular analysis domain *d*. Then the logit transformation of P_d, commonly referred to as the "log odds," is defined as

$$L = \ln[P_d / (1 - P_d)],$$

where "1n" denotes the natural logarithm.

Letting $\hat{p}_d$ be the estimate of the domain proportion, the log odds estimate becomes

$$\hat{L} = \ln[\hat{p}_d / (1 - \hat{p}_d)].$$

The lower and upper confidence limits of *L* are formed as

$$A = \hat{L} - K\left[\frac{\sqrt{\text{var}(\hat{p}_d)}}{\hat{p}_d(1 - \hat{p}_d)}\right],$$

$$B = \hat{L} + K\left[\frac{\sqrt{\text{var}(\hat{p}_d)}}{\hat{p}_d(1 - \hat{p}_d)}\right],$$

where $\text{var}(\hat{p}_d)$ is the variance estimate of $\hat{p}_d$, the quantity in brackets is a first-order Taylor series approximation of the standard error of $\hat{L}$, and *K* is the critical value of the *t*-distribution associated with a specified level of confidence and degrees of freedom (*df*). For example, to produce 95 percent confidence limits for 2016 national estimates, the value of *K* would be 1.96

based on 750 *df*. See Section 6 for more details on what *df* should be used for various subpopulations in order to determine *K* appropriately.

Although the distribution of the logit-transformed estimate, $\hat{L}$, is asymptotically normal, the variance term in the CI is estimated, and a critical value from the *t*-distribution is therefore appropriate when calculating CIs. A sufficiently large sample size is required for the asymptotic properties to take effect, and this is usually determined through the suppression criteria applied to the estimates (see Section 10).

Applying the inverse logit transformation to *A* and *B* above yields a CI for $\hat{p}_d$ as follows:

$$\hat{p}_{d,lower} = \frac{1}{1+\exp(-A)},$$

$$\hat{p}_{d,upper} = \frac{1}{1+\exp(-B)},$$

where "exp" denotes the inverse log transformation. The lower and upper CI endpoints for percentage estimates are obtained by multiplying the lower and upper endpoints of $\hat{p}_d$ by 100.

The CI for the estimated domain total, $\hat{Y}_d$, as estimated by

$$\hat{Y}_d = \hat{N}_d \cdot \hat{p}_d,$$

is obtained by multiplying the lower and upper limits of the proportion CI by $\hat{N}_d$. For domain totals $\hat{Y}_d$, where $\hat{N}_d$ (weighted population total) is not fixed, the CI approximation assumes that the sampling variation in $\hat{N}_d$ is negligible relative to the sampling variation in $\hat{p}_d$.

Examples below illustrate how to compute and use CIs of prevalence estimates. *Note that CIs of totals cannot be computed using published data from the detailed tables because this computation requires the weighted sum of the measures, which is most often not a published estimate.* In Appendix A, see Exhibit A.24 for example SUDAAN® Software for Statistical Analysis of Correlated Data (RTI International, 2012) code and Exhibit A.25 for example Stata® code (StataCorp, 2015) on how to compute the CIs of the totals. The example in Section 8.1 computes CIs using the formulas shown above, the Section 8.2 example computes CIs using Excel, the Section 8.3 example shows how to use the CIs to compute standard errors, and the Section 8.4 example shows how to use Excel to compute the standard error from the CIs.

8.1 Example of Calculating Confidence Intervals Using Published Prevalence Estimates and Standard Errors

The following example illustrates how to determine the 95 percent CI using the prevalence estimates and standard errors provided for measures shown in the detailed tables.

This example will use estimates from Table 1.1B of the 2015 detailed tables (Center for Behavioral Health Statistics and Quality, 2016d), which displays the prevalence for lifetime, past year, and past month illicit drug use.[35] This example will focus on 2015 past year pain reliever use. Pain reliever use shown in Table 1.1B has a prevalence estimate of 4.7 percent in 2015. The corresponding standard error shown in Table 1.1D is 0.11 percent for 2015. This example uses the formulas shown above to determine the 95 percent CI for the prevalence estimate of past year pain reliever use in 2015. Note that

$$\text{var}(\hat{p}_d) = (SE(\hat{p}_d))^2; thus, \sqrt{\text{var}(\hat{p}_d)} = SE(\hat{p}_d).$$

Define log odds estimate:

$$\hat{L} = \ln[0.047 / (1 - 0.047)] = -3.0095.$$

Define the upper and lower confidence limits of the log odds:

$$A = -3.0095 - 1.96\left[\frac{0.0011}{0.0448}\right] = -3.0577$$

$$B = -3.0095 + 1.96\left[\frac{0.0011}{0.0448}\right] = -2.9613.$$

Apply inverse logit transformation to yield CIs *p*:

$$\hat{p}_{d,lower} = \frac{1}{1+\exp(3.0577)} = 0.0449$$

$$\hat{p}_{d,upper} = \frac{1}{1+\exp(2.9613)} = 0.0492.$$

Rounding to two significant digits, the 95 percent CI is 4.5 percent to 4.9 percent.

The same CI calculated using SUDAAN is also 4.4 percent to 4.9 percent. The slight difference is a rounding error due to the reduced number of significant digits shown in the published estimates. However, the results are usually close. Producing the CIs for totals requires the weighted sum, which is generally not published. For examples using SUDAAN or Stata to calculate CIs for means and totals, see Exhibits A.24 and A.25, respectively.

[35] Although this example references estimates from the 2015 detailed tables, similar examples can be found in the 2016 detailed tables.

8.2 Example of Calculating Confidence Intervals in Excel Using Published Prevalence Estimates and Standard Errors

Using the same estimates presented in Section 8.1, this example uses Excel functions to produce the same CIs produced in the previous example. Recall that $\text{var}(\hat{p}_d) = (\text{SE}(\hat{p}_d))^2$; thus, $\sqrt{\text{var}(\hat{p}_d)} = \text{SE}(\hat{p}_d)$. Excel can be used to set up a simple table (shown below) to produce the CI. Cells A2 through D2 are the known values input by the user. Cells E2 and F2 contain functions. This table could extend over several rows to aid in producing many CIs (i.e., data for columns A through D would have to be entered for each row, and then the formulas in columns E and F could be copied for all rows).

	A	B	C	D	E	F
1	p_d	SE(p_d)	α	*df*	$p_{d,lower}$	$p_{d,upper}$
2	0.047	0.0011	0.05	750	0.0449	0.0492

The lower confidence limit is determined using the extended formula for $\hat{p}_{d,lower}$.

	A	B	C	D	E	F
1	p_d	SE(p_d)	α	*df*	$p_{d,lower}$	$p_{d,upper}$
2	0.047	0.0011	0.05	750	=1/(1+EXP(-(LN(A2/(1-A2)) - T.INV.2T(C2,D2)*(B2/(A2*(1-A2)))))))	0.0492

The upper limit is determined using the extended formula for $\hat{p}_{d,upper}$.

	A	B	C	D	E	F
1	p_d	SE(p_d)	α	*df*	$p_{d,lower}$	$p_{d,upper}$
2	0.047	0.0011	0.05	750	0.0449	=1/(1+EXP(-(LN(A2/(1-A2)) + T.INV.2T(C2,D2)*(B2/(A2*(1-A2)))))))

The 95 percent CI is 4.4 percent to 4.9 percent.

In the Excel formulas for $\hat{p}_{d,lower}$ and $\hat{p}_{d,upper}$, the Excel function T.INV.2T calculates the inverse of the two-tailed Student's *T*-Distribution, a continuous probability distribution. The function arguments are T.INV.2T (probability, *df*), where probability is the probability (between 0 and 1) for which the user would want to evaluate the inverse of the two-tailed Student's *T*-Distribution. This is also sometimes referred to as the alpha level. For 95 percent CIs, the alpha level is always 0.05. The example uses 750 *df* for a national estimate, but this could be adjusted for smaller areas of estimation.

8.3 Example of Calculating Standard Errors Using Published Confidence Intervals

This example illustrates how to determine the standard error for an estimate when only the prevalence and 95 percent CI are provided. If a NSDUH publication provided only the prevalence estimate for 2015 past year pain reliever use (4.7 percent) and the 95 percent CI (4.4 percent to 4.9 percent), the reader may want to determine the standard error for use in

significance testing. This example uses the formulas above to determine the standard error for the prevalence estimate of past year pain reliever use in 2015.[36] Note that

$$\text{var}(\hat{p}_d) = (\text{SE}(\hat{p}_d))^2; \text{ thus, } \sqrt{\text{var}(\hat{p}_d)} = \text{SE}(\hat{p}_d).$$

Following is the formula to calculate A (lower CI for log odds estimate) using the lower CI of the prevalence estimate (p).

$$\hat{p}_{d,lower} = \frac{1}{1+\exp(-A)}; \text{ thus, } A = \ln\left(\frac{\hat{p}_{d,lower}}{1-\hat{p}_{d,lower}}\right).$$

$$\text{Ln}\left(\frac{0.047}{1-0.047}\right) = -3.0095$$

Below is the formula for A (lower limit of the log odds ratio). To get the standard error, convert this formula as follows.

$$\text{A} = \hat{\text{L}} - \text{K}\left[\frac{\sqrt{\text{var}(\hat{\text{p}}_\text{d})}}{\hat{\text{p}}_\text{d}(1-\hat{\text{p}}_\text{d})}\right]; \textit{thus}, SE(\hat{\text{p}}_\text{d}) = \frac{(\text{A} - \hat{\text{L}})(\hat{\text{p}}_\text{d}(1-\hat{\text{p}}_\text{d}))}{-\text{K}}.$$

Recall from the Section 8.1 example that $\hat{\text{L}} = -3.0095$. Thus, the standard error is computed as follows:

$$SE(\hat{P}_d) = \frac{(-3.0577 + 3.0095)(0.047(1-0.047))}{-1.96} = 0.0011 \text{ or } 0.11\%.$$

Using similar steps, the standard error can be produced from the upper CI with the formulas below. Note that the denominator is positive in the standard error formula when using the upper CI.

$$\text{B} = \ln\left(\frac{\hat{\text{p}}_{\text{d,upper}}}{1-\hat{\text{p}}_{\text{d,upper}}}\right) \textit{ and } SE(\hat{\text{p}}_\text{d}) = \frac{(\text{B} - \hat{\text{L}})(\hat{\text{p}}_\text{d}(1-\hat{\text{p}}_\text{d}))}{\text{K}}$$

$$\text{B} = -2.9613 \text{ and } SE(\hat{\text{p}}_\text{d}) = 0.0011, \text{ or } 0.11 \text{ percent}$$

As previously mentioned, 2015 Table 1.1D shows that the actual standard error when calculated in SUDAAN is 0.11 percent, which is the same as the calculated 0.11 percent. *Note that the reduced number of significant digits shown in the published estimates may cause rounding errors when producing standard errors from the lower or upper limits of the CIs.* This can result in standard error estimates that differ when compared with the SUDAAN-calculated

[36] Although this example references estimates from the 2015 detailed tables, similar examples can be found in the 2016 detailed tables.

standard error. However, standard errors calculated from the lower or upper limits usually will provide the same testing results as tests performed in SUDAAN, except results may differ when the *p* value is close to the predetermined level of significance.

8.4 Example of Calculating Standard Errors in Excel Using Published Confidence Intervals

Using the same estimates presented in Section 8.3, this example uses Excel functions to produce the same standard errors from the previous example (i.e., the SUDAAN-generated standard error from Table 1.1D). Recall that $\text{var}(\hat{p}_d) = (\text{SE}(\hat{p}_d))^2$; thus, $\sqrt{\text{var}(\hat{p}_d)} = \text{SE}(\hat{p}_d)$. Excel can be used to set up a simple table (shown below) to produce the standard error from the upper and lower limits of the CI. Cells A2 through D2 are the known values input by the user. Cell E2 contains the function to determine the standard error. This table could extend over several rows to aid in producing many standard errors (i.e., data for columns A through D would have to be entered for each row, and then the formula in column E could be copied for all rows). Note that once the methods used in this example have determined the standard error from the CI, the methods shown in the Section 7.6 example can be used to perform independent *t* tests for differences of reported estimates in Excel.

Calculate the standard error from the lower limit of the CI:

	A	B	C	D	E
1	p_d	$p_{d,lower}$	α	*df*	$SE(p_d)$
2	0.047	0.0449	0.05	750	0.0011

$\text{SE}(\hat{p}_d) = 0.0011$, or 0.11 percent.

Similar to the Section 8.2 example, the Excel function T.INV.2T is used in the formula to determine the standard error.

	A	B	C	D	E
1	p_d	$p_{d,lower}$	α	*df*	$SE(p_d)$
2	0.047	0.0449	0.05	750	=(((LN(B2/(1-B2)))-(LN(A2/(1-A2))))*(A2*(1-A2)))/(-T.INV.2T(C2,D2))

Calculate the standard error from the upper limit of the CI:

	A	B	C	D	E
1	p_d	$p_{d,upper}$	α	*df*	$SE(p_d)$
2	0.047	0.0492	0.05	750	0.0011

$\text{SE}(\hat{p}_d) = 0.0011$, or 0.11 percent.

This also requires the use of the Excel function T.INV.2T (see details in Section 8.2).

	A	B	C	D	E
1	p_d	$p_{d,upper}$	α	*df*	$SE(p_d)$
2	0.047	0.0492	0.05	750	=(((LN(B2/(1-B2)))-(LN(A2/(1-A2))))*(A2*(1-A2)))/(T.INV.2T(C2,D2))

Remember that the reduced number of significant digits shown in the published estimates may cause rounding errors when producing standard errors. This can result in standard error estimates that differ when using the lower or upper limit when compared with the SUDAAN-calculated standard error. However, standard errors calculated from the lower or upper limits usually will provide the same testing results as tests performed in SUDAAN, except results may differ when the *p* value is close to the predetermined level of significance.

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9. Initiation Estimates

Since its inception in the 2004 National Survey on Drug Use and Health (NSDUH), past year initiation refers to respondents whose date of first use of a particular substance (or misuse of psychotherapeutic drugs) was within the 12 months before their interview date. Beginning in 2015, based on questionnaire changes regarding use and misuse of psychotherapeutic drugs (pain relievers, tranquilizers, stimulants, and sedatives), past year initiation for these psychotherapeutic drugs now refers to the first time that misuse occurred rather than a respondent's first use.[37] Past year initiation is determined by self-reported past year use, age at first use, year and month of recent new use, and the interview date.[38]

Since 1999, the survey questionnaire has collected year and month of first use for recent initiates (i.e., individuals who used a particular substance for the first time at their current age or the year before their current age). Month, day, and year of birth also are obtained directly or are imputed for item nonrespondents as part of the data postprocessing. Additionally, the computer-assisted interviewing instrument records and provides the date of the interview.

The calculation of past year initiation does not take into account whether the respondent initiated substance use while a resident of the United States. This method of calculation has little effect on past year estimates and provides direct comparability with other standard measures of substance use because the populations of interest for the measures will be the same (i.e., both measures examine all possible respondents and do not restrict to those only initiating substance use in the United States).

One important note for initiation estimates is the relationship between a main substance category and subcategories of substances (e.g., hallucinogens would be a main category, and LSD, phencyclidine [PCP], and Ecstasy would be subcategories in relation to hallucinogens). For most measures of substance use, any member of a subcategory is by necessity a member of the main category (e.g., if a respondent is a past month user of Ecstasy, then he or she is also a past month user of any hallucinogen). However, this is not the case with regard to estimates for the initiation of substances. *Because an individual can only be an initiate of a particular substance category (main or sub) a single time, a respondent with lifetime use of a subcategory may not, by necessity, be included as an initiate of the corresponding main category, even if he or she were an initiate for a different subcategory.* For example, an individual can initiate use of any hallucinogen, LSD, PCP, or Ecstasy only once. A respondent who initiated use of any hallucinogen more than 12 months ago by definition is not a past year initiate of hallucinogen use, even if he or she initiated use of LSD, PCP, or Ecstasy in the past year. For prescription drugs, please see below for specifics on how initiation is defined.

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[37] For brevity, "misuse" is not repeated in every instance that text refers to first use. Readers are advised that terms such as "past year use" and "first use" that are used in the remainder of this section for substance use in general refer to *misuse* for prescription psychotherapeutic drugs.

[38] "Self-reported" refers to responses provided by the respondents within the questionnaire. Responses are imputed for respondents who do not self-report for these items. Day-of-first-use data are imputed because this information is not asked in the questionnaire.

In addition to estimates of the number of people initiating use of a substance in the past year, estimates of the mean age of past year first-time users of these substances were computed. *In some detailed tables, estimates of the mean age at initiation in the past 12 months have been restricted to people aged 12 to 49 so that the mean age estimates reported are not influenced by those few respondents who were past year initiates at age 50 or older.* As a measure of central tendency, means are influenced heavily by the presence of extreme values in the data, and this age constraint of 12 to 49 should increase the utility of these results to health researchers and analysts by providing a better picture of the substance use initiation behaviors among the U.S. civilian, noninstitutionalized population. This constraint was applied only to estimates of mean age at first use and does not affect estimates of initiation.

9.1 Initiation of Misuse of Prescription Psychotherapeutic Drugs

Starting in the 2015 NSDUH, respondents were asked about the initiation of misuse of prescription psychotherapeutic drugs only for the individual prescription drugs that they had misused in the past 12 months. If respondents reported initiation of one or more prescription drugs at an age or in a year and month that was more than 12 months before the interview date, they logically were not past year initiates for misuse of any drug in that psychotherapeutic category (e.g., pain relievers). If respondents reported only past year initiation of the drugs that they misused in the past 12 months, they were asked a follow-up question to determine whether they ever misused any drug in that category more than 12 months before the interview.[39] *Therefore, unlike the situation for other substances in NSDUH (see below), respondents' status as past year initiates of misuse of any psychotherapeutic drug in an overall category was determined principally through their answers to the relevant follow-up question.*

If respondents answered the follow-up question as "yes," then they were defined as *not* being past year initiates for the overall category; the affirmative response indicated that respondents had misused one or more other drugs in the category more than 12 months ago. Respondents who answered the follow-up question as "no" *were* defined as past year initiates for the overall entire category; the negative response indicated that these respondents did not misuse any other drug in that category more than 12 months ago. If respondents answered the follow-up question on initiation as "don't know" or "refused," then their status as a past year initiate (or not) was resolved through imputation.

Because of this question structure for identifying individuals who initiated misuse of any psychotherapeutic drug in a given category in the past year, measures of the age and date of first misuse of any psychotherapeutic drug in that category were created only for respondents who were past year initiates. If past year initiates had no missing data for the age, year, and month when they first misused any drug in that category, then the age, year, and month of first misuse logically were assigned from the earliest reports.[40] If past year initiates did not know or refused to report the age when they first misused some drugs in that category, but they reported first

[39] Respondents also were asked the follow-up question if the sum of the reports of past year initiation plus missing data for initiation equaled the number of specific drugs that they misused in the past year (i.e., and there were no reports of initiation of misuse more than 12 months before the interview date).

[40] The questionnaire included items for the age, year, and month of first misuse for each individual psychotherapeutic drug that respondents misused in the past year. A day of first misuse was imputed for past year initiates.

misuse of at least one psychotherapeutic drug in the category at the age that was 1 year younger than their current age, then it nevertheless could be logically inferred that this was the age when these past year initiates first misused any drug in that category. Similarly, if past year initiates did not know or refused to report the year when they first misused some drugs in that category but they reported first misuse of at least one psychotherapeutic drug in the previous calendar year (e.g., 2015 for respondents in the 2016 NSDUH), then it could be logically inferred that respondents initiated misuse of any drug in that category in the previous calendar year. If it was not possible to assign a definite age, year, and month of first misuse for a past year initiate based on the respondent's questionnaire data, then these values were assigned through imputation.

The total number of past year initiates of misuse of any psychotherapeutic drug in a category can be used in the estimation of percentages among (1) all individuals in the population (or all individuals in a subgroup of the population, such as individuals in a given age group) and (2) individuals who were past year users of the substance. The 2016 NSDUH detailed tables show estimates for these two percentages (Center for Behavioral Health Statistics and Quality [CBHSQ], 2017f). Because of the change in focus starting with the 2015 NSDUH questions for specific psychotherapeutic drugs from the lifetime to the past year period, respondents who last misused any prescription psychotherapeutic drug in a category more than 12 months ago may underreport misuse. This is especially true if they are not presented with examples of drugs that formerly were available by prescription in the United States but are no longer available. These respondents who did not report misuse that occurred more than 12 months ago would be misclassified as still being "at risk" for initiation of misuse of prescription drugs in that psychotherapeutic category (i.e., individuals who initiated misuse more than 12 months ago are no longer at risk for initiation). *For this reason, the 2016 detailed tables do not show percentages for initiation of misuse of psychotherapeutic drugs among individuals who were at risk for initiation.* For more information on the impact of the 2015 survey changes on the initiation of the prescription drug misuse, please see Section A.4.3 in Appendix A of the prescription drug use and misuse in the United States report (Hughes et al., 2016).

9.2 Initiation of Use of Substances Other Than Prescription Psychotherapeutic Drugs

For substances other than prescription psychotherapeutic drugs (i.e., cigarettes, smokeless tobacco, cigars, alcohol, cocaine, crack cocaine, heroin, hallucinogens, inhalants, and methamphetamine), past year initiation among people using a substance in the past year can be viewed as an indicator variable defined as follows:

$$I_{(\text{Past Year Initiate})} \text{ if } [(\text{MM/DD/YYYY})_{\text{Interview}} - (\text{MM/DD/YYYY})_{\text{First Use of Substance}}] \leq 365 ,$$

Where $(\text{MM/DD/YYYY})_{\text{Interview}}$ denotes the month, day, and year of the interview, and $(\text{MM/DD/YYYY})_{\text{First Use of Substance}}$ denotes the date of first use. The total number of past year initiates can be used in the estimation of different percentages. For these substances, denominators for the percentages vary according to whether estimates are being calculated for (1) all individuals in the population (or all individuals in a subgroup of the population, such as individuals in a given age group), (2) individuals who are at risk for initiation because they have

not used the substance of interest before the past 12 months, or (3) past year users of the substance. The detailed tables show all three of these percentages.

Note that the 12-month reference period (i.e., 365 days) is set up on the calendar at the beginning of the audio computer-assisted self-interviewing portion of the computer-assisted interview. For example, if the date of the interview (DOI) is December 1, 2016 (12/01/2016), then 365 days earlier would be December 1, 2015 (12/01/2015). If a respondent's date of first use is the same as the DOI, then the respondent is considered a past year initiate (because I = 0). Additionally, in this example, a respondent interviewed on 12/01/2016 could have used for the first time as far back as 12/01/2015 and be considered a past year initiate.

Potential Undercoverage of Past Year Initiates

Because NSDUH respondents are aged 12 or older at the time of the interview, younger individuals (younger than 12 years) in the sample dwelling units are not eligible for selection into the NSDUH sample. *Some of these younger people may have initiated substance use during the past year. As a result, past year initiate estimates suffer from undercoverage when one can think of the estimates as reflecting all initial users regardless of current age.* For substance use estimates in 2016 that are comparable with those in earlier years,[41] data can be obtained retrospectively based on the age at and date of first use. As an example, people who were 12 years old on the date of their interview in the 2016 survey may have reported initiating use of cigarettes between 1 and 2 years ago; these people would have been past year initiates reported in the 2015 survey had people who were 11 years old on the date of the 2015 interview been allowed to participate in the survey. Similarly, estimates of past year use by younger people (aged 10 or younger) can be derived from the current survey, but they apply to initiation in prior years—not the survey year.

To get a rough estimate of the potential undercoverage of individuals younger than 12 years in the current year, reports of substance use initiation reported by people aged 12 or older were estimated for the years in which these people would have been 1 to 11 years younger. These estimates do not necessarily reflect behavior by people who were 1 to 11 years younger in the current survey. Instead, the data for the 11-year-olds reflect initiation in the year before the current survey, the data for the 10-year-olds reflect behavior between the 12th and 23rd month before this year's survey, and so on. A crude way to adjust for the difference in the years that the estimate pertains to without considering changes to the population is to apply an adjustment factor to each age-based estimate of past year initiates. The adjustment factor can be based on a ratio of lifetime users aged 12 to 17 in the current survey year to the same estimates for the prior applicable survey year. To illustrate the calculation, consider past year use of alcohol. In the 2015 survey, 73,115 youths who were 12 years old were estimated to have initiated use of alcohol between 1 and 2 years earlier.[42] These youths would have been past year initiates in the 2014 survey conducted on the same dates had the 2014 survey covered younger people. The estimated number of lifetime users currently aged 12 to 17 was 7,074,614 for 2015 and 7,375,125 for 2014, indicating fewer overall initiates of alcohol use among people aged 17 or

[41] Briefly, CBHSQ considers estimates in 2015 and 2016 to be comparable with those in 2002 to 2014 for cigarettes, cigars, alcohol (any use), marijuana, cocaine, crack cocaine, and heroin.

[42] Although this example references estimates from the 2015 detailed tables, similar examples can be found in the 2016 detailed tables.

younger in 2015. Thus, an adjusted estimate of initiation of alcohol use by people who were 11 years old in 2015 is given by

$$(\text{Estimated Past Year Initiates Aged 11})_{2014} \times \frac{(\text{Estimated Lifetime Users Aged 12 to 17})_{2015}}{(\text{Estimated Lifetime Users Aged 12 to 17})_{2014}}.$$

This yielded an adjusted estimate of 70,136 people who were 11 years old on a 2015 survey date and initiated use of alcohol in the past year:

$$73{,}115 \times \frac{7{,}074{,}614}{7{,}375{,}125} = 70{,}136.$$

A similar procedure was used to adjust the estimated number of past year initiates among respondents who would have been 10 years old on the same month and day of the month as the interview date in 2013 and for younger individuals in earlier years. The overall adjusted estimate for past year initiates of alcohol use by youths aged 11 or younger on the date of the interview in 2013 was 123,673, or about 2.6 percent of the estimate based on past year initiation by people aged 12 or older only (123,673 ÷ 4,760,846 = 0.0260). Based on similar analyses, the estimated undercoverage of past year initiates by youths aged 11 or younger on the date of the 2013 interview was 2.6 percent for cigarettes and 1.2 percent for marijuana.

The undercoverage of past year initiates aged 11 or younger also affects the mean age-at-first-use estimate. An adjusted estimate of the mean age at first use was calculated using a weighted estimate of the mean age at first use based on the 2015 survey and the numbers of youths aged 11 or younger in the past year obtained in the aforementioned analysis for estimating undercoverage of past year initiates. Analysis results based on the 2014 and 2015 NSDUHs showed that the mean age at first use was changed from 17.6 to 17.4 for alcohol, from 17.9 to 17.6 for cigarettes, and from 19.0 to 18.9 for marijuana. The decreases reported above are comparable with results generated in prior survey years as well as results generated for the 2016 survey year. Based on the 2016 NSDUH, alcohol changed from 17.4 to 17.1, cigarettes from 18.0 to 17.8, and marijuana from 19.3 to 19.2 as described in more detail in section B.4.2 of the 2016 methodological summary and definitions (CBHSQ, 2017a).

Similar analysis results for inhalants, methamphetamine, ecstasy, and overall hallucinogens are not available for 2015 because changes to the questions affected the comparability of estimates between 2014 and 2015 (see Section 2.2). Specific information about undercoverage for inhalants using 2016 data can be found in Section B.4.2 of the 2016 methodological summary and definitions (CBHSQ, 2017a).

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10. Suppression of Estimates with Low Precision

Direct survey estimates that were considered to be unreliable because of unacceptably large sampling errors were not reported, but rather were noted by an asterisk (*). *The criteria used to assess the need to suppress direct survey estimates were based on prevalence (for proportion estimates), the relative standard error (RSE) (defined as the ratio of the standard error [SE] over the estimate), nominal (actual) sample size, and effective sample size for each estimate.*

Proportion estimates ($\hat{p}$) within the range $0 < \hat{p} < 1,$ and corresponding estimated numbers of users, were suppressed if

$$\text{RSE}[-\ln(\hat{p})] > .175 \text{ when } \hat{p} \leq .5$$

or

$$\text{RSE}[-\ln(1-\hat{p})] > .175 \text{ when } \hat{p} > .5\,.$$

The choice of .175 is arbitrary, but it roughly marks the tails of the distribution.

Based on a first-order Taylor series approximation of $\text{RSE}[-\ln(\hat{p})]$ and $\text{RSE}[-\ln(1-\hat{p})],$ the following equation was derived and used for computational purposes when applying a suppression rule dependent on effective sample sizes:

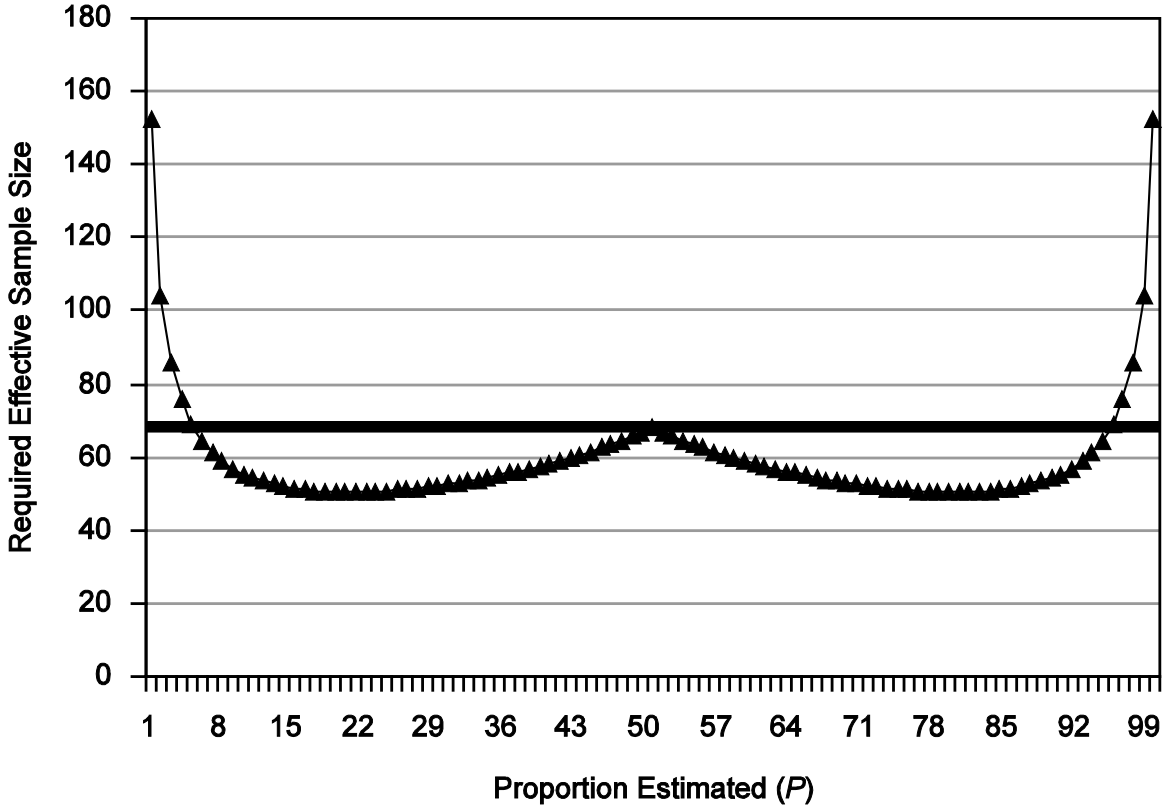
$$\frac{\text{SE}(\hat{p})/\hat{p}}{-\ln(\hat{p})} > .175 \text{ when } \hat{p} \leq .5$$

or

$$\frac{\text{SE}(\hat{p})/(1-\hat{p})}{-\ln(1-\hat{p})} > .175 \text{ when } \hat{p} > .5\,.$$

The separate formulas for $\hat{p} \leq .5$ and $\hat{p} > .5$ produce a symmetric suppression rule; that is, if $\hat{p}$ is suppressed, $1-\hat{p}$ will be suppressed as well. See Figure 10.1 for a graphical representation of the required minimum effective sample sizes as a function of the proportion estimated. When $.05 < \hat{p} < .95,$ the symmetric properties of the rule produce local minimum effective sample sizes at $\hat{p} = .2$ and again at $\hat{p} = .8,$ such that an effective sample size of greater than 50 is required; this means that estimates would be suppressed for these values of $\hat{p}$ unless the effective sample sizes were greater than 50. Within this same interval of $.05 < \hat{p} < .95,$ a local maximum effective sample size of 68 is required at $\hat{p} = .5.$

Figure 10.1 Required Effective Sample in the 2016 NSDUH as a Function of the Proportion Estimated



These varying effective sample size requirements sometimes produced unusual occurrences of suppression for a particular combination of prevalence estimates. For example, in some cases, lifetime prevalence estimates near $\hat{p} = .5$ were suppressed (effective sample size was less than 68 but greater than 50), while not suppressing the corresponding past year or past month estimates near $\hat{p} = .2$ (effective sample sizes greater than 50). *To reduce the occurrence of this type of inconsistency and to maintain a conservative suppression rule, estimates of* $\hat{p}$ *between .05 and .95, which had effective sample sizes below 68, were suppressed starting with the 2000 National Survey on Drug Use and Health (NSDUH).*

The effective sample size for a domain is a function of the nominal sample size and the design effect (i.e., nominal sample size/design effect). During the original development of this suppression rule, the design effect was calculated outside SUDAAN® Software for Statistical Analysis of Correlated Data (RTI International, 2012) in SAS® (SAS Institute, 2017). Since the 2005 NSDUH analysis, the direct SUDAAN design effect was used to provide a more precise and accurate reflection of the design effect (because of the removal of several possible rounding errors) when compared with the SAS method used in the past. The differences between the direct SUDAAN design effects and the SAS-calculated design effects occur only at approximately the tenth decimal place or later; however, previously published estimates that were on the borderline of being suppressed or unsuppressed because of the effective sample size suppression rule may potentially change from suppressed to unsuppressed, or vice versa.

Design effects range widely among the measures and domains found in the detailed tables. Potential problems with suppression occur only if large design effects are combined with small domains. Large estimates of design effects when resulting from small sample sizes (variability of the variance estimate) should be suppressed on effective sample size alone, and the rule above achieves this. *But to protect against unreliable estimates caused by small design effects and small nominal sample sizes, a minimum nominal sample size suppression criterion (n = 100) was employed starting with the 2000 NSDUH.* Table 10.1 shows a formula for calculating design effects. *Prevalence estimates also were suppressed if they were close to 0 or 100 percent (i.e., if* $\hat{p} < .00005$ *or if* $\hat{p} > .99995$*).*

Table 10.1 Summary of 2016 NSDUH Suppression Rules

Estimate	Suppress if:
Prevalence Estimate, $\hat{p}$, with Nominal Sample Size, *n*, and Design Effect, *deff* $\left(deff = \frac{n[\mathrm{SE}(\hat{p})]^2}{\hat{p}(1-\hat{p})} \right)$	(1) The estimated prevalence estimate, $\hat{p}$, is < 0.00005 or > 0.99995,[1] or (2) $\frac{\mathrm{SE}(\hat{p}) \ / \ \hat{p}}{-\ln(\hat{p})} > 0.175$ when $\hat{p} \le 0.5$, or $\frac{\mathrm{SE}(\hat{p}) \ / \ (1-\hat{p})}{-\ln(1-\hat{p})} > .175$ when $\hat{p} > 0.5$, or (3) Effective *n* < 68, where $Effective\ n = \frac{n}{deff} = \frac{\hat{p}(1-\hat{p})}{\left[\mathrm{SE}(\hat{p})\right]^2}$, or (4) *n* < 100. Note: The rounding portion of this suppression rule for prevalence estimates will produce some estimates that round at one decimal place to 0.0 or 100.0 percent but are not suppressed from the tables.[2]
Estimated Number (Numerator of $\hat{p}$)	The estimated prevalence estimate, $\hat{p}$, is suppressed. Note: In some instances when $\hat{p}$ is not suppressed, the estimated number may appear as a 0 in the tables. This means that the estimate is greater than 0 but less than 500 (estimated numbers are shown in thousands). Note: In some instances when totals corresponding to several different means that are displayed in the same table and some, but not all, of those means are suppressed, the totals will not be suppressed. When all means are suppressed, the totals will also be suppressed.
Means not bounded between 0 and 1 (i.e., Mean Age at First Use, Mean Number of Drinks), $\bar{x}$, with Nominal Sample Size, *n*	(1) $\mathrm{RSE}(\bar{x}) > 0.5$, or (2) *n* < 10.

deff = design effect; RSE = relative standard error; SE = standard error.

NOTE: The suppression rules included in this table are used for detecting unreliable estimates and are sufficient for confidentiality purposes in the context of the first findings reports and detailed tables.

[1] Starting with the 2015 NSDUH, the close to 100 percent portion of the rule was changed to $\hat{p} > 0.99995$ instead of the old rule, which was greater than or equal to 0.99995. This was done so the close to 0 and close to 100 rule were both strict inequalities.

[2] See Sections 3 and 7 of this report for more information on rounding.

Source: SAMHSA, Center for Behavioral Health Statistics and Quality, National Survey on Drug Use and Health, 2016.

Beginning with the 1991 survey, the suppression rule for proportions based on $\text{RSE}[-\ln(\hat{p})]$ described above replaced an older rule in which data were suppressed whenever $\text{RSE}(\hat{p}) > .5$. This rule was changed because the older rule imposed a very stringent application for small $\hat{p}$, but a very lax application for large $\hat{p}$. The new rule ensured a more uniformly stringent application across the whole range of $\hat{p}$ (i.e., from 0 to 1). The old rule also was asymmetric in the sense that suppression only occurred in terms of $\hat{p}$; that is, there was no complementary rule for $(1 - \hat{p})$, which the new suppression rules now account for.

Estimates of totals were suppressed if the corresponding prevalence estimates were suppressed. Estimates of means not bounded between 0 and 1 (e.g., mean age at first use, mean number of drinks consumed) were suppressed if the RSEs of the estimates were larger than .5 or if the sample sizes were smaller than 10 respondents. This rule was based on an empirical examination of the estimates of mean age of first use and their SEs for various empirical sample sizes. *Although arbitrary, a sample size of 10 appears to provide sufficient precision and still allow reporting by year of first use for many substances.* In these cases, the totals (e.g., total number of drinks consumed) were suppressed if the corresponding mean estimates were suppressed.

Section 4 of the detailed tables demonstrates an exception to the rule that indicates the totals are suppressed when their corresponding means are suppressed. Some tables in Section 4 of the detailed tables show estimates of initiation among different populations. Specifically, these Section 4 tables display the number of initiates among three different populations: the total population, people at risk for initiation, and past year users.[43] In these tables, some mean estimates may be suppressed whereas the total estimate is not suppressed. When at least one mean estimate in the table is not suppressed, one can assume that the numerator (or total estimate) is not the cause for the suppression and the total estimate will not be suppressed. In contrast, when all mean estimates are suppressed, the total will also be suppressed.

Tables that show sample sizes and population counts do not incorporate the suppression rule for several reasons. One reason is that no mean is associated with these estimates; thus, most of the components of the suppression criteria are not applicable. Also, because no behavior associated with the numbers is displayed, there is no risk of behavior disclosure.

The suppression criteria for various NSDUH estimates are summarized in Table 10.1, and sample SAS code based on both SAS and SUDAAN output and Stata® code (StataCorp, 2015) demonstrating how to implement these rules can be found in Appendix A (Exhibits A.7 through A.9).

[43] Starting in 2015, the prescription pain reliever, prescription tranquilizer, prescription stimulant, and prescription sedative Section 4 tables do not show estimates for people at risk for initiation.

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Appendix A: Documentation for Conducting Various Statistical Procedures: SAS®, SUDAAN®, and Stata® Examples

This appendix provides guidance concerning various options that should be specified in SAS® (SAS Institute, 2017), SUDAAN® Software for Statistical Analysis of Correlated Data (RTI International, 2012), and Stata® (StataCorp, 2015) to correctly analyze the National Survey on Drug Use and Health (NSDUH) data. Additionally, example SAS, SUDAAN, and Stata code is provided to illustrate how the information in this report is applied to generate estimates (means, totals, and percentages, along with the standard errors [SEs]), implement the suppression rule, perform statistical tests of differences, handle missing data, calculate confidence intervals, test between overlapping domains, test independence of two variables, perform pairwise tests, and perform linear trend tests. Specifically, examples using 2013 and 2014 NSDUH data are included in this appendix that produce estimates of past month alcohol use by year (2013 and 2014) and gender (males and females) using the statistical procedures documented within this report and implemented in the 2014 detailed tables (Center for Behavioral Health Statistics and Quality [CBHSQ], 2015c, 2015d).[44] The following examples are created using variable names found on the restricted-use dataset; thus, some variable names may differ when using the public use file (see footnote 5 for more detail). Note that all the detailed tables are produced using survey analysis procedures in SUDAAN and accompanying auxiliary SAS code. However, the following Stata and SAS survey analysis code replicates results from these tables. Please note that a corresponding SAS exhibit has not been provided for all examples in the appendix, but SAS procedures could be used to produce similar results. The exhibit number for each example, a description of the example, and a reference to the report section that addresses the example are provided in Table A.1.

Table A.1 Summary of SUDAAN, Stata, and SAS Exhibits

SUDAAN/ SAS Exhibit	Stata Exhibit	SAS Exhibit	Description	Report Section
A.1	A.2	A.3	Produces estimates (including means, totals, and the respective standard errors) using single year or pooled year data.	Sections 3, 5, and 6
A.4	A.5	A.6	Calculates the standard error of the total for controlled domains using the estimates produced in Exhibits A.1 through A.3.	Section 5
A.7	A.8	A.9	Creates suppression indicators for each estimate (i.e., suppression rule).	Section 10
A.10	A.11		Performs statistical tests of differences between means.	Section 7
A.12	A.13		Calculates the *p* value for the test of differences between uncontrolled totals (using estimates produced in Exhibits A.10 and A.11).	Section 7
A.14, A.16, A.18, and A.20	A.15, A.17, A.19, and A.21		Calculates the *p* value for the test of differences between controlled domains by producing the covariance matrix, pulling the relevant covariance components, and calculating the variances.	Section 7
A.22	A.23		Produces estimates where the variable of interest has missing values.	Section 4

(continued)

[44] Although the appendix examples reference the 2013 and 2014 data from the 2014 detailed tables, these examples apply to the 2015 and 2016 data from the 2016 detailed tables and other NSDUH survey years.

Table A.1 Summary of SUDAAN, Stata, and SAS Exhibits (continued)

SUDAAN/ SAS Exhibit	Stata Exhibit	SAS Exhibit	Description	Report Section
A.24	A.25		Calculates a confidence interval using estimates produced in Exhibits A.1 and A.2.	Section 8
A.26	A.27		Calculates percentages and the associated standard errors.	Sections 3 and 5
A.28	A.29		Performs statistical tests of differences between two groups when the two groups overlap.	Section 7
A.30	A.31		Performs tests of the independence of the prevalence variable and subgroup variable.	Section 7
A.32	A.33		Performs pairwise tests for each subgroup variable found significant in Exhibits A.30 and A.31.	Section 7
A.34	A.35		Performs linear trend test of significance across years using test statements.	Section 7
A.36	A.37		Performs linear trend test of significance across years using modeling.	Section 7

NOTE: An empty cell indicates that no example is provided for that specific topic.

Guide for Defining Options for Analyzing NSDUH Data

Before running the SUDAAN procedures, the input dataset must be sorted by the nesting variables (VESTR and VEREP), or the NOTSORTED option must be used for SUDAAN to create an internal copy of the input dataset properly sorted by the nesting variables. The SUDAAN procedure DESCRIPT can then be run to produce weighted (using ANALWT for restricted-use data files, ANALWT_C for public use files, or a pooled weight created for calculating annual averages) and unweighted sample sizes, means, totals, SEs of means and totals, and *p* values for testing of the means and totals.

Stata and SAS commands can be run without the data being sorted. The Stata commands svy: mean and svy: total will be used throughout in these exhibits, and it should be noted that Stata code is case sensitive. The SAS procedure SURVEYMEANS will be used in Exhibit A.3. Note that Stata and SAS still use VESTR and VEREP as nesting variables; however, as previously noted, the data do not need to be sorted.

The following options are specified within the SUDAAN, Stata, and SAS examples to correctly produce estimates using NSDUH data.

Design

Because of the complex NSDUH sample design, estimates are calculated using a method in SUDAAN that is unbiased for linear statistics. This method is based on multistage clustered sample designs where the first-stage (primary) sampling units are drawn with replacement. In SUDAAN, a user must specify DESIGN=WR (meaning with replacement). Note that with Stata and SAS, the design does not need to be indicated, because the svyset command in Stata and the SURVEYMEANS procedure in SAS use Taylor linearized variance estimation as a default.

Nesting Variables

The NSDUH nesting variables (VESTR and VEREP) are used to capture explicit stratification and to identify clustering with the NSDUH data, which are needed to compute the

variance estimates correctly. Two replicates per year were defined within each variance stratum (VESTR). Each variance replicate (VEREP) consists of four segments, one for each quarter of data collection. One replicate consists of those segments that are "phasing out" or will not be used in the next survey year. The other replicate consists of those segments that are "phasing in" or will be fielded again the following year, thus constituting the 50 percent overlap between survey years. A segment stays in the same VEREP for the 2 years it is in the sample. This simplifies computing SEs for estimates based on combined data from adjacent survey years. In SUDAAN, users must use the NEST statement within one of the appropriate SUDAAN procedures. In the NEST statement, the variable for the variance stratum should be listed first, followed by the primary sampling unit variable; that is, the VESTR variable should be listed first, followed by the VEREP variable. In Stata, the nesting variables are specified in the svyset command. In SAS, users must use the STRATA and CLUSTER statements within one of the appropriate SAS procedures. VESTR should be listed in the STRATA statement and VEREP should be listed in the CLUSTER statement. Unlike the svyset command in Stata where it only needs to be called once, the NEST statement in SUDAAN and the STRATA and CLUSTER statements in SAS will need to be used each time a user calls one of the appropriate SUDAAN or SAS procedures, respectively.

Degrees of Freedom

As described in Section 6 of this report, the degrees of freedom (DDF in SUDAAN and dof in Stata) are 750 for the 2016 national estimates, 144 in California; 120 each in Florida, New York, and Texas; 96 each in Illinois, Michigan, Ohio, and Pennsylvania; 60 each in Georgia, New Jersey, North Carolina, and Virginia; and 48 each in the remaining 38 states and the District of Columbia. For an analysis of a group of states, the degrees of freedom can be less than or equal to the sum of the degrees of freedom for each individual state due to overlap of variance strata. The specific number of degrees of freedom can be computed by counting the unique values of VESTR for the particular geographic area of interest. The technique of counting the number of unique values of VESTR can also be used for analyses combining survey data across years. When combining any years of data (i.e., 2015 and 2016), the degrees of freedom remain the same as if it were a single year (e.g., 750 for national estimates) when these years are part of the same sample design. When comparing estimates in two domains with different degrees of freedom, err on the conservative side and use the smaller degrees of freedom. To specify the degrees of freedom in SUDAAN, the DDF = option on the procedure statement is used. This option should be used each time one of the appropriate SUDAAN procedures is called to ensure correct calculations. In Stata, the degrees of freedom are specified as a design option in the svyset command (i.e., "dof(750)"). If switching from national estimates to state estimates, the svyset command would need to be rerun with the updated degrees of freedom. The provided SAS exhibits do not include testing or calculation of confidence intervals; therefore, options for specifying degrees of freedom are not shown. If a user is using SAS to calculate confidence intervals or conduct testing, the degrees of freedom should be specified as appropriate. More information about which degrees of freedom to use can be found in Section 6.

Design Effect

The option DEFT4 within SUDAAN provides the correct measure of variance inflation due to stratification (or blocking), clustering, and unequal weighting in NSDUH estimation.

Requesting deff srssubpop in Stata gives the same result as using DEFT4 in SUDAAN. The design effect cannot be output directly from the SURVEYMEANS procedure in SAS. In the following exhibits, the UNIVARIATE procedure with the VARDEFF=WGT option is used to calculate the variance under simple random sampling correctly.

The following examples apply the specific NSDUH options described previously to compute estimates, apply the suppression rule, and perform significance testing by using the data produced by the examples in Exhibit A.1 (using SUDAAN code), Exhibit A.2 (using Stata code), and Exhibit A.3 (using SAS code). Please note that the data produced by the example in Exhibit A.3 are only used to calculate estimates and standard errors and to apply the suppression rule.

Generation of Estimates

Exhibits A.1 through A.3 demonstrate how to compute various types of estimates for past month alcohol use by year and gender for single year or combined year (pooled) data using the SUDAAN descript procedure, the Stata svy: mean and svy: total commands, and the SAS SURVEYMEANS procedure, respectively. The SUDAAN example includes code to compute the prevalence estimate (MEAN), SE of the mean (SEMEAN), weighted sample size (WSUM), unweighted sample size (NSUM), weighted total (TOTAL), and SE of the totals (SETOTAL). The Stata svy: mean and svy: total commands and the SAS SURVEYMEANS procedure will produce the same estimates. Whether the SETOTAL is taken directly from SUDAAN, Stata, or SAS depends on whether the specified domain (i.e., gender in this example) is among those forced to match their respective U.S. Census Bureau population estimates through the weight calibration process. See the Standard Errors section below for additional information. For more information on how to create a pooled weight to use when producing annual averages of combined years of data, see Section 3.

Exhibit A.1 SUDAAN DESCRIPT Procedure (Estimate Generation: Single Year and Pooled Years of Data)

```
PROC SORT DATA=DATANAME; /*SAS code to sort output dataset by
Nesting Variables*/
BY VESTR VEREP;
RUN;

PROC DESCRIPT DATA=DATANAME DDF=750 DESIGN=WR FILETYPE=SAS DEFT4;
/*Alternatively, the DOF may change if using combined data based
on whether or not the combined years cross survey designs*/
NEST VESTR VEREP;
WEIGHT ANALWT;  /*Standard single-year, person-level analysis
weight. Alternatively, a created pooled weight could be used here
to produce annual averages based on combined years of data.*/
VAR ALCMON;  /*Past month alcohol analysis variable*/
SUBGROUP YEAR IRSEX;
     /*Year variable, where 2013=1 & 2014=2. Alternatively, the
     year variable could identify the combined years of data,
     i.e., 2011 and 2012 = 1 & 2013 and 2014 = 2*/
     /*Gender variable, where male=1 & female=2*/
LEVELS 2 2;
TABLES YEAR*IRSEX; /*Gender by year*/
PRINT WSUM NSUM MEAN SEMEAN TOTAL SETOTAL / REPLACE STYLE=NCHS;
OUTPUT WSUM MEAN SEMEAN TOTAL SETOTAL NSUM DEFFMEAN /REPLACE
   NSUMFMT=F8.0 WSUMFMT=F12.0 MEANFMT=F15.10 SEMEANFMT=F15.10
   DEFFMEANFMT=F15.10 TOTALFMT=F12.0 SETOTALFMT=F12.0
   FILENAME="OUT.SUDFILE";
TITLE "ESTIMATES OF PAST MONTH ALCOHOL BY YEAR AND GENDER";
RUN;
```

Note: The following CLASS statement could be used in place of SUBGROUP and LEVELS statements in the above example:

```
CLASS YEAR IRSEX;
```

Exhibit A.2 Stata COMMANDS svy: mean and svy: total (Estimate Generation: Single Year and Pooled Years of Data)

```
use using ".\\dataname.dta", clear

/*Ensure all variables are lower case*/
rename *, lower

/*ID Nesting variables (VESTR and VEREP) and weight variable (ANALWT -
standard single-year, person-level analysis weight). Alternatively, a created
pooled weight could be used here to produce annual averages based on combined
years of data. The DOF may also change if using combined data based on
whether or not the combined years cross survey designs*/
svyset verep [pw=analwt], strata(vestr) dof(750)

gen total_out=.
gen setotal=.
gen mean_out=.
gen semean=.
gen nsum=.
gen wsum=.
gen deffmean=.

/*Estimated means of past month alcohol use by year and gender*/

 /*Year variable, where 2013=1 & 2014=2. Alternatively, the year variable
could identify the combined years of data, i.e., 2011 and 2012 = 1 & 2013 and
2014 = 2 */
 /*Gender variable, where male=1 & female=2*/
svy: mean alcmon, over(year irsex)
matrix M=e(b) /*Store mean estimates in matrix M*/
matrix S=e(V) /*Store variances in matrix S*/
matrix N=e(_N) /*Store sample size in matrix N*/
matrix W=e(_N_subp) /*Store weighted sample size in matrix W*/

estat effects, deff srssubpop/*Obtain design effect*/
matrix D=e(deff) /*Store design effect in matrix D*/

/*Extract values stored in the M, S, N, W, and D matrices defined above to
the mean_out, semean, nsum, wsum, and deffmean variables. The loop ensures
that the appropriate values are extracted for each value of year and
gender.*/
 local counter=1
  forvalues i=1/2 { /*number of years*/
   forvalues j=1/2 { /* number of gender categories*/
       replace mean_out=(M[1,'counter']) if year=='i' & irsex=='j'
       replace semean=(sqrt(S['counter','counter'])) ///

if year=='i' & irsex=='j'
       replace nsum=(N[1,'counter']) if year=='i' & irsex=='j'
       replace wsum=(W[1,'counter']) if year=='i' & irsex=='j'
       replace deffmean=(D[1,'counter']) if year=='i' & irsex=='j'
 local counter='counter'+1
   }
  }
```

Exhibit A.2 Stata COMMANDS svy: mean and svy: total (Estimate Generation: Single Year and Pooled Years of Data) (continued)

```
/*Estimated Totals*/
svy: total alcmon, over(year irsex)

 matrix M=e(b) /*Store total estimates in matrix M*/
 matrix S=e(V) /*Store variances in matrix S*/

/*Extract values stored in the M and S     matrices defined above to the
total_out and setotal variables. The loop ensures that the appropriate values
are extracted for value of year and gender.*/

 local counter=1
  forvalues i=1/2 { /*number of years*/
   forvalues j=1/2 { /* number of gender categories*/
    replace total_out=(M[1,'counter']) if year=='i' & irsex=='j'
    replace setotal=(sqrt(S['counter','counter'])) ///
if year=='i' & irsex=='j'
  local counter='counter'+1
   }
  }

keep wsum mean_out semean total_out setotal nsum deffmean year irsex

duplicates drop year irsex, force /*keep one record per subpopulation
                                    of interest*/

/*Format wsum, mean_out, semean, total_out, setotal, nsum, and deffmean
variables to control appearance in output.*/

format wsum %-12.0fc
format mean_out %-15.10f
format semean %-15.10f
format total_out %-12.0fc
format setotal %-12.0fc
format nsum %-8.0fc
format deffmean %-15.10f

/*Estimates of past month alcohol by year and gender*/
list year irsex wsum nsum mean_out semean total_out setotal

/*The output from this exhibit will be utilized in Exhibit A.19. Users can
either rerun the code presented in this exhibit or save the output from this
exhibit to a dataset using the following command.*/
save ".\\EXa2.dta" , replace
```

Exhibit A.3 SAS SURVEYMEANS Procedure (Estimate Generation: Single Year and Pooled Years of Data)

```
TITLE "ESTIMATES OF PAST MONTH ALCOHOL BY YEAR AND GENDER";
PROC SURVEYMEANS DATA=DATANAME SUMWGT NOBS MEAN SUM;
STRATA VESTR;  /*Nesting variable - strata*/
CLUSTER VEREP;  /*Nesting variable - PSU*/
WEIGHT ANALWT;  /*Standard single-year, person-level analysis
weight. Alternatively, a created pooled weight could be used here
to produce annual averages based on combined years of data.*/
VAR ALCMON;  /*Past month alcohol analysis variable*/
DOMAIN YEAR*IRSEX;  /*Gender by year*/
     /*Year variable, where 2013=1 & 2014=2. Alternatively, the
     year variable could identify the combined years of data,
     i.e., 2011 and 2012 = 1 & 2013 and 2014 = 2*/
     /*Gender variable, where male=1 & female=2*/
ODS OUTPUT DOMAIN=OUT.SASFILE;
RUN;
```

Standard Errors

As discussed in Section 5 of this report, the SE for the mean (or proportion) comes directly out of SUDAAN and SAS in the output variables SEMEAN (Exhibit A.1) and STDERR (Exhibit A.3), respectively, and the SEMEAN is calculated in Stata by taking the square root of the variance (Exhibit A.2). However, to compute the SE of the totals, NSDUH implements different methods depending on whether the specified domain (i.e., gender in this example) is controlled or uncontrolled through poststratification during the weighting process. For the 2016 detailed tables (CBHSQ, 2017f), Table 5.1 in Section 5 contains a list of what are considered controlled domains. If a domain is uncontrolled (e.g., not forced to match the U.S. Census Bureau population estimates), then the SE of the total comes directly out of SUDAAN and SAS in the output variables SETOTAL and STDDEV, respectively. If the domain is controlled (e.g., forced to match the U.S. Census Bureau population estimates), then the SE of the total is calculated as SETOTAL (SE of controlled domain) = WSUM (weighted sample size) × SEMEAN (SE for the mean/proportion). Because gender is controlled, the SE of the totals would not be taken directly from the examples in Exhibits A.1 through A.3 but rather would be computed using the formula shown in Exhibits A.4 through A.6 (note that the formula is the same in all three exhibits) (Exhibits A.1 and A.4 using SUDAAN/SAS code, Exhibits A.2 and A.5 using Stata code, and Exhibits A.3 and A.6 using SAS code).

Exhibit A.4 SAS Code Based on SUDAAN Output (Calculation of Standard Error of Totals for Controlled Domains)

```
DATA ESTIMATE;
SET OUT.SUDFILE; /*input the output file from above SUDAAN
                   procedure*/
/************************************************************
 Define SETOTAL for gender because it is a controlled domain.
  In the SUDAAN procedure in Exhibit A.1, IRSEX is in the
subgroup
     Statement with 2 levels indicated. Therefore, values for
     0=total male & females, 1=males, and 2=females are
     automatically produced.
************************************************************/

IF IRSEX IN (0,1,2) THEN SETOTAL=WSUM*SEMEAN;

RUN;
```

Exhibit A.5 Stata Code (Calculation of Standard Error of Totals for Controlled Domains)

```
generate setotal2=wsum*semean
replace setotal = setotal2 if inlist(irsex,1,2)
/*Note, Stata does not automatically produce overall estimates,
i.e., irsex=0*/
```

Exhibit A.6 SAS Code Based on SAS Output (Calculation of Standard Error of Totals for Controlled Domains)

```
DATA SASEST;
SET OUT.SASFILE; /*input the output file from above SAS procedure
in Exhibit A.3 */

IF IRSEX IN (1,2) THEN SETOTAL=SUMWGT*STDERR;
/*Note, SAS does not automatically produce overall estimates,
i.e., irsex=0*/

RUN;
```

Suppression Rule

As described in Section 10 of this report, each published NSDUH estimate goes through a suppression rule to detect if the estimate is unreliable because of an unacceptably large sampling error. The suppression rules as they apply to different types of estimates are shown in Table 10.1 in Section 10. The examples in Exhibits A.7 (SAS code based on SUDAAN output), A.8 (Stata code), and A.9 (SAS code) show the prevalence estimate rule and the rule for means not bounded by 0 and 1 (i.e., averages). The average suppression rule is commented out for these examples, but it would replace the prevalence estimate suppression rule if averages were shown in the examples in place of means bounded by 0 and 1. Note that Exhibit A.9 also calculates the design effect, which cannot be directly obtained from the SAS SURVEYMEANS procedure in Exhibit A.3.

Exhibit A.7 SAS Code Based on SUDAAN Output (Implementation of Suppression Rule)

```
      DATA ESTIMATE;
      SET OUT.SUDFILE; /*input the output file from above Exhibit A.1
SUDAAN procedure*/

      /******APPLY THE PREVALENCE ESTIMATE SUPPRESSION RULE*******/

      /* CALCULATE THE RELATIVE STANDARD ERROR */
            IF MEAN GT 0.0 THEN RSE=SEMEAN/MEAN;

      /* CALCULATE THE RELATIVE STANDARD ERROR OF NATURAL LOG P */
            IF 0.0 LT MEAN LE 0.5 THEN RSELNP=RSE/ABS(LOG(MEAN));
            ELSE IF 0.5 LT MEAN LT 1.0 THEN
            RSELNP=RSE*(MEAN/(1-MEAN))/(ABS(LOG(1-MEAN)));

      /*CALCULATE THE EFFECTIVE SAMPLE SIZE*/
            EFFNSUM=NSUM/DEFFMEAN;

      /*SUPPRESSION RULE FOR PREVALENCE ESTIMATES*/
      IF (MEAN LT 0.00005) OR (MEAN GT 0.99995) OR (RSELNP GT 0.175) OR
      (EFFNSUM < 68) OR (NSUM <100) THEN SUPRULE=1;

      /*SUPPRESSION RULE FOR MEANS NOT BOUNDED BY 0 AND 1, I.E.
      AVERAGES (COMMENTED OUT FOR THIS EXAMPLE)*/
      /*IF (RSE GT 0.5) OR (NSUM < 10) THEN SUPRULE=1;*/

      RUN;
```

Exhibit A.8 Stata Code (Implementation of Suppression Rule)

```
/******APPLY THE PREVALENCE ESTIMATE SUPPRESSION RULE*******/

/*CALCULATE THE RELATIVE STANDARD ERROR*/
generate rse=.
replace rse=semean/mean_out ///
if mean_out > 0.0 & !missing(mean_out)

/* CALCULATE THE RELATIVE STANDARD ERROR OF NATURAL LOG P */
generate rselnp=.
replace rselnp=rse/(abs(log(mean_out))) ///
if mean_out <= 0.5 & mean_out > 0.0
replace rselnp=rse*(mean_out/(1-mean_out)) ///
/(abs(log(1-mean_out))) if mean_out < 1.0 & mean_out > 0.5

/*CALCULATE THE EFFECTIVE SAMPLE SIZE*/
generate effnsum=nsum/deffmean

/*SUPPRESSION RULE FOR PREVALENCE ESTIMATES*/
generate suprule1a=1 if rselnp > 0.175 & !missing(rselnp)
generate suprule1b=1 if mean_out <.00005 & !missing(mean_out)
generate suprule1c=1 if mean_out >.99995 & !missing(mean_out)
generate suprule2=1 if effnsum < 68 & !missing(nsum)
generate suprule3=1 if nsum < 100 & !missing(nsum)

generate supress=0
replace supress=1 if suprule1a==1 | suprule1b==1 | ///
suprule1c==1 | suprule2==1 | suprule3==1

/*SUPPRESSION RULE FOR MEANS NOT BOUNDED BY 0 AND 1, I.E.
AVERAGES
(COMMENTED OUT FOR THIS EXAMPLE)*/
/*generate suprule=1 if (nsum < 10 & !missing(nsum))///
| (rse > 0.5 & !missing(rse))*/
```

Exhibit A.9 SAS Code Based on SAS Output (Implementation of Suppression Rule)

```
PROC SORT DATA = DATANAME; /*Sort output dataset by domain
variables*/
BY YEAR IRSEX;
RUN;

/*Calculate the variance under simple random sampling*/
PROC UNIVARIATE DATA=DATANAME VARDEF=WGT;
VAR ALCMON;
WEIGHT ANALWT; /*Standard single-year, person-level analysis
weight*/
BY YEAR IRSEX; /*Gender by year*/
ODS OUTPUT MOMENTS=SASUNI;
RUN;

/*Manipulate dataset output from PROC UNIVARIATE to keep only the
domain variables and the standard error*/
DATA DEFF (RENAME = (NVALUE1 = SESRS) KEEP = YEAR IRSEX NVALUE1);
SET SASUNI;
WHERE LABEL1 = "Std Deviation";
RUN;

/*Merge with dataset output in Exhibit A.3 */
DATA SASEST_MERGE;
MERGE OUT.SASFILE DEFF;
BY YEAR IRSEX;
RUN;

DATA SASEST;
SET SASEST_MERGE;

/*Calculate DEFF of the mean*/
DEFFMEAN = (STDERR/SESRS)**2*(N-1);

/******APPLY THE PREVALENCE ESTIMATE SUPPRESSION RULE*******/
/* CALCULATE THE RELATIVE STANDARD ERROR */
IF MEAN GT 0.0 THEN RSE=STDERR/MEAN;

/* CALCULATE THE RELATIVE STANDARD ERROR OF NATURAL LOG P */
IF 0.0 LT MEAN LE 0.5 THEN RSELNP=RSE/ABS(LOG(MEAN));
ELSE IF 0.5 LT MEAN LT 1.0 THEN RSELNP=RSE*(MEAN/(1-
MEAN))/(ABS(LOG(1-MEAN)));

/*CALCULATE THE EFFECTIVE SAMPLE SIZE*/
EFFNSUM=N/DEFFMEAN;

/*SUPPRESSION RULE FOR PREVALENCE ESTIMATES*/
IF (MEAN LT 0.00005) OR (MEAN GT 0.99995) OR (RSELNP GT 0.175) OR
(EFFNSUM < 68) OR (N <100) THEN SUPRULE=1;
```

Exhibit A.9 SAS Code Based on SAS Output (Implementation of Suppression Rule) (continued)

```
/*SUPPRESSION RULE FOR MEANS NOT BOUNDED BY 0 AND 1, I.E.
AVERAGES (COMMENTED OUT FOR THIS EXAMPLE)*/
/*IF (RSE GT 0.5) OR (N < 10) THEN SUPRULE=1;*/

RUN;
```

For tables that display totals along with multiple means from differing populations (e.g., initiation tables in Section 4 of the 2014 detailed tables [CBHSQ, 2015c]), suppression is not as straightforward as coding the rule in the SAS/SUDAAN or Stata programs. As discussed in Section 10, perhaps some means are suppressed and others are not suppressed. In that instance, suppression of the total estimate is based on the level of suppression present across all corresponding mean estimates. If all mean estimates associated with a total estimate are suppressed, the total estimate should also be suppressed. If at least one mean estimate is not suppressed, the total estimate is also not suppressed. The best way to ensure that this happens is to program the total estimate in the table to be suppressed if, and only if, the mean with the largest denominator is suppressed. The analyst should also check the final table to ensure that the suppression follows the rule after the program has been run.

Statistical Tests of Differences

As described in Section 7 of this report, significance tests were conducted on differences of prevalence estimates between the 2016 NSDUH and previous years of NSDUH back to 2002. For the 2016 detailed tables (CBHSQ, 2017f), no combined data were presented. Note that for year-to-year tests of differences, if the estimate for either year is suppressed, then the resulting *p* value is also suppressed. This is the rule used when creating the detailed tables; however, this code does not show this rule being implemented.

For the SUDAAN example (Exhibit A.10), testing of differences requires a separate PROC DESCRIPT run from the initial DESCRIPT run that produces the corresponding yearly estimates. Tests of differences can be generated using DESCRIPT's CONTRAST, PAIRWISE, or DIFFVAR statements. The SUDAAN example (Exhibit A.10) uses the DIFFVAR statement to test for differences between two years (i.e., 2013 and 2014) of past month alcohol use estimates for all people aged 12 or older (IRSEX=0), all males (IRSEX=1), and all females (IRSEX=2). It also includes an example of using multiple DIFFVAR statements to test for differences between each year (i.e., 2002–2013) and the current year in this example (i.e., 2014). Similarly, for the Stata example (Exhibit A.11), a separate svy: mean command is needed.

Similar to computing the SEs of the totals, calculating *p* values for tests of differences of totals differs depending on whether an estimate is considered to be from a controlled domain or an uncontrolled domain. Both ways are described as follows with accompanying example code: Exhibits A.10 and A.12 show example code for uncontrolled domains using SUDAAN and auxiliary SAS, and Exhibits A.11 and A.13 show the same examples using Stata. Exhibits A.10, A.14, A.16, A.18, and A.20 show example code for controlled domains using SUDAAN and SAS, and Exhibits A.11, A.15, A.17, A.19, and A.21 show the same examples using Stata.

Exhibit A.10 SUDAAN DESCRIPT Procedure (Tests of Differences)

```
PROC DESCRIPT DATA=DATANAME DDF=750 DESIGN=WR FILETYPE=SAS;
NEST VESTR VEREP;
WEIGHT ANALWT;
VAR ALCMON;
SUBGROUP YEAR IRSEX;
LEVELS 2 2;
TABLES IRSEX;
DIFFVAR YEAR=(1 2) / NAME="2013 vs 2014";
PRINT WSUM NSUM MEAN SEMEAN TOTAL SETOTAL T_MEAN P_MEAN /
  REPLACE STYLE=NCHS;
OUTPUT WSUM MEAN SEMEAN TOTAL SETOTAL NSUM T_MEAN P_MEAN /
   REPLACE
   NSUMFMT=F8.0 WSUMFMT=F12.0 MEANFMT=F15.10 SEMEANFMT=F15.10
   TOTALFMT=F12.0 SETOTALFMT=F12.0 FILENAME="OUT.SUDTESTS";
TITLE "TESTS OF DIFFERENCES BETWEEN 2013 AND 2014 ESTIMATES OF
PAST MONTH ALCOHOL BY GENDER";
RUN;
```

Note: For testing of multiple years vs the current year as shown in Multiyear Detailed Tables, more years could be included in the data (and LEVELS statement) and several DIFFVAR statements as shown below could be used in place of the single DIFFVAR statement in the above example:

```
LEVELS 13 2;
DIFFVAR YEAR=(1 13) /NAME="2002 vs 2014";
DIFFVAR YEAR=(2 13) /NAME="2003 vs 2014";
DIFFVAR YEAR=(3 13) /NAME="2004 vs 2014";
DIFFVAR YEAR=(4 13) /NAME="2005 vs 2014";
DIFFVAR YEAR=(5 13) /NAME="2006 vs 2014";
DIFFVAR YEAR=(6 13) /NAME="2007 vs 2014";
DIFFVAR YEAR=(7 13) /NAME="2008 vs 2014";
DIFFVAR YEAR=(8 13) /NAME="2009 vs 2014";
DIFFVAR YEAR=(9 13) /NAME="2010 vs 2014";
DIFFVAR YEAR=(10 13) /NAME="2011 vs 2014";
DIFFVAR YEAR=(11 13) /NAME="2012 vs 2014";
DIFFVAR YEAR=(12 13) /NAME="2013 vs 2014";

TITLE "TESTS OF DIFFERENCES BETWEEN EACH YEAR AND 2014 ESTIMATES
OF PAST MONTH ALCOHOL BY GENDER";
```

Note: The following CLASS statement could be used in place of SUBGROUP and LEVELS statements in the above examples:

```
CLASS YEAR IRSEX;
```

When one or more contrasts are specified in SUDAAN, as in the DIFFVAR statement above, the output variable MEAN becomes the contrast mean where the number assigned to the output variable, CONTRAST, represents the tests in order of appearance in the SAS code, and SEMEAN becomes the SE of the contrast mean. The examples above also output the *t*-statistic (T_MEAN) and the corresponding *p* value (P_MEAN).

SUDAAN does not test differences in the corresponding totals explicitly. However, it will output the contrast total (TOTAL) and the SE of the contrast total (SETOTAL). With these statistics and the correct degrees of freedom (750 in this example), the *p* value (PVALT) for the test of differences between totals for uncontrolled domains can be calculated as indicated in Exhibit A.12. The SAS function PROBT returns the probability from a *t*-distribution.

Exhibit A.11 Stata COMMANDS svy: mean and svy: total (Tests of Differences)

```
use using ".\\dataname.dta", clear

/*Ensure all variables are lower case*/
rename *, lower

/*ID Nesting variables (VESTR and VEREP) and weight variable
(ANALWT - standard single-year, person-level analysis weight)*/
svyset verep [pweight=analwt], strata(vestr) dof(750)
{
svy: mean alcmon, over(year irsex)
local max=2*2 /*number of years*number of gender categories. This
is the total number of supops*/
local range=2 /*number of gender categories. This is the number
of subpops per year*/
local compmin='max'-'range'
gen pmean=. /*P-value T-test Cont. Mean=0*/
local counter=1
forvalues i=1/1 { /*number of contrasts needed to compare year==1
vs year==2*/
      local counter2=1
      forvalues j=1/2 { /*number of gender categories*/
            local stop='counter2'+'compmin'
            test [alcmon]_subpop_'counter' = ///
            [alcmon]_subpop_'stop', nosvyadjust
            replace pmean=r(p) if year=='i' & irsex=='j' /*p-value
      t-test cont. mean=0*/
            local counter='counter'+1
            local counter2='counter2'+1
      }
            }
      }
```

Exhibit A.11 Stata COMMANDS svy: mean and svy: total (Tests of Differences) (continued)

```
svy: total alcmon, over(year irsex)
      {
matrix M = e(b) /*The totals for each subpopulation are stored in
here*/
local max=2*2     /*number of years*number of gender categories.
This is the total number of supops*/
local range=2    /*number of gender categories. This is the number
of subpops per year*/
local compmin='max'-'range'
gen total_out=. /*Contrast total*/
gen setotal=.    /*Total Standard error*/
      local counter=1
      forvalues i=1/1 { /*number of contrasts needed to compare
year==1 vs year==2*/
            local counter2=1
            forvalues j=1/2 {     /*number of gender categories*/
                  local stop='counter2'+'compmin'
                  test [alcmon]_subpop_'counter' = ///
      [alcmon]_subpop_'stop', nosvyadjust matvlc(test'counter')

                  replace setotal= sqrt((test'counter'[1,1])) ///
      if year=='i' & irsex=='j'
                  replace total_out=M[1,'counter']-M[1,'stop'] ///
      if year=='i' & irsex=='j' /*Calculating the difference
between the totals of the subpopulation*/
                  local counter='counter'+1
                  local counter2='counter2'+1
                  }
            }
      }

      *Keeping variables that match SUDAAN
      keep irsex total_out setotal pmean
      duplicates drop irsex total_out setotal pmean, force /*keep
one record per contrast*/

      drop if total_out ==. /* drop the rows where there is no
information */
      format pmean %-15.10f
      format total_out %-12.0fc
      format setotal %-12.0fc

      /* Output the dataset*/
      list irsex total_out setotal pmean
```

Exhibit A.11 Stata COMMANDS svy: mean and svy: total (Tests of Differences) (continued)

Note: For testing of multiple years vs the current year as shown in Multiyear Detailed Tables, more years could be included in the data and the number of tests conducted can be increased by changing the number of for loops as shown below. The first block of code applies to means while the second block of code applies to totals. Note, this only demonstrates how the for loops would change. The svy: statements demonstrated above would still need to be utilized.

```
local max=13*2 /*number of years*number of gender categories.
This is the total number of subpops*/
local range=2 /*number of gender categories. This is the number
of subpops per year*/
local compmin='max'-'range'
gen pmean=. /*P-value T-test Cont. Mean=0*/
local counter=1
forvalues i=1/12 { /*number of contrasts needed to compare each
year to the current year*/
      local counter2=1
      forvalues j=1/2 { /*number of gender categories*/
            local stop='counter2'+'compmin'
            test [alcmon]_subpop_'counter' = ///
            [alcmon]_subpop_'stop', nosvyadjust
            replace pmean=r(p) if year=='i' & irsex=='j' /*p-value
      t-test cont. mean=0*/
            local counter='counter'+1
            local counter2='counter2'+1
      }
            }
      }

local max=13*2 /*number of years*number of gender categories.
This is the total number of subpops.*/
local range=2 /*number of gender categories. This is the number
of subpops per year.*/
local compmin='max'-'range'
gen total=. /*Contrast total*/
gen setotal=. /*Total Standard error*/
local counter=1
forvalues i=1/12 { /*number of contrasts needed to compare each
year to the current year*/
      local counter2=1
      forvalues j=1/2 { /*number of gender categories*/
            local stop='counter2'+'compmin'
            test [alcmon]_subpop_'counter' = ///
       [alcmon]_subpop_'stop', nosvyadjust ///
       matvlc(test'counter')
            replace setotal= sqrt((test'counter'[1,1])) if ///
       year=='i' & irsex=='j'
            replace total=M[1,'counter']-M[1,'stop'] if ///
```

Exhibit A.11 Stata COMMANDS svy: mean and svy: total (Tests of Differences) (continued)

```
      year=='i' & irsex=='j' /*Calculating the difference between
the totals of the subpopulation*/
            local counter='counter'+1
            local counter2='counter2'+1
            }
      }
}
```

Exhibit A.12 SAS Code Based on SUDAAN Output (Calculation of the *P* Value for the Test of Differences between Totals for Uncontrolled Domains)

```
IF SETOTAL GT 0.0 THEN DO; /*SETOTAL and TOTAL come from
Exhibit A.10*/
  PVALT=2*(1-PROBT(ABS(TOTAL/SETOTAL),750));
END;
```

Exhibit A.13 Stata Code (Calculation of the *P* Value for the Test of Differences between Totals for Uncontrolled Domains)

```
generate pvalt = tprob(750,abs(total_out /setotal)) ///
if setotal > 0 & !missing(setotal) /* two-tail*/
/*total_out and setotal come from Exhibit A.11.
*/
```

In Exhibits A.1 and A.2, all people aged 12 or older and both genders are annually controlled totals. For controlled domains like these, additional steps are needed to compute similar *p* values for tests of differences. One approach uses an additional DESCRIPT procedure in SUDAAN to output the appropriate covariance matrix (Exhibit A.14), and an additional svy: mean command in Stata outputs a similar matrix (Exhibit A.15). Then, through further SAS or Stata data manipulations, the weighted sample sizes (WSUM), variances, and the covariance of the two means (obtained from the covariance matrix) are used to generate the standard *t* test statistic. The corresponding *p* value can once again be produced using the SAS PROBT function or Stata TPROB function and calculated *t* test statistic.

Exhibit A.14 SUDAAN DESCRIPT Procedure (Covariance Matrix)

```
PROC DESCRIPT DATA=DATANAME DDF=750 DESIGN=WR FILETYPE=SAS DEFT4;
NEST VESTR VEREP;
WEIGHT ANALWT;
VAR ALCMON;
SUBGROUP YEAR IRSEX;
LEVELS 2 2;
TABLES IRSEX*YEAR;
PRINT COVMEAN / STYLE = NCHS;
OUTPUT / MEANCOV = DEFAULT REPLACE FILENAME="OUT.SUDCOV";
TITLE "Variance Covariance Matrices";
RUN;
```

Exhibit A.14 SUDAAN DESCRIPT Procedure (Covariance Matrix) (continued)

```
Note: The following CLASS statement could be used in place of SUBGROUP
and LEVELS statements in the above example:
     CLASS YEAR IRSEX;
```

Exhibit A.15 Stata COMMAND svy: mean (Covariance Matrix)

```
use using ".\\dataname.dta", clear

/*Ensure all variables are lower case*/
rename *, lower

/*ID Nesting variables (VESTR and VEREP) and weight variable
(ANALWT - standard single-year, person-level analysis weight)*/

svyset verep [pweight=analwt], strata(vestr) dof(750)
svy: mean alcmon, over(year irsex)
*Save and display the Covariance Matrix
matrix M = e(V)
matrix list M
```

The covariances of the estimated means can be obtained from the output of the DESCRIPT procedure (Exhibit A.14) and svy: mean command (Exhibit A.15). The covariance matrix in SUDAAN consists of a row and column for each gender (total, male, female) and year (both years; i.e., 2013 and 2014) combination with each cell corresponding to a particular variance component (i.e., a 9 x 9 matrix). Because the rows and columns of the matrix are identical, the cells in the top half (above the diagonal) and the bottom half (below the diagonal) are identical. Table A.2 shows a shell for what the SUDAAN covariance matrix would look like for this example. The Stata matrix would look similar but with a few exceptions: total rows and columns would not be included (i.e., year=0 and irsex=0), and the order would be reversed (i.e., year would be listed first, followed by irsex). Table A.3 presents the Stata matrix shell.

Table A.2 SUDAAN Matrix Shell

			IRSEX=0			IRSEX=1			IRSEX=2		
			YEAR=0	YEAR=1	YEAR=2	YEAR=0	YEAR=1	YEAR=2	YEAR=0	YEAR=1	YEAR=2
		ROWNUM	B01	B02	B03	B04	B05	B06	B07	B08	B09
IRSEX=0	YEAR=0	1									
	YEAR=1	2									
	YEAR=2	3									
IRSEX=1	YEAR=0	4									
	YEAR=1	5									
	YEAR=2	6									
IRSEX=2	YEAR=0	7									
	YEAR=1	8									
	YEAR=2	9									

Table A.3 Stata Matrix Shell

OVER:	YEAR	IRSEX
_subpop_1:	1	1
_subpop_2:	1	2
_subpop_3:	2	1
_subpop_4:	2	2

	alcmon: _subpop_1	alcmon: _subpop_2	alcmon: _subpop_3	alcmon: _subpop_4
alcmon:_subpop_1				
alcmon:_subpop_2				
alcmon:_subpop_3				
alcmon:_subpop_4				

In the SUDAAN output, each cell of the variance-covariance matrix is identified by a separate variable of the form B0*x*, where *x* is a particular cell number. (Cells are numbered left to right.) The variable *ROWNUM* is an additional output variable that simply identifies the matrix row. The covariance data needed for a particular significance test can be pulled out of the matrix using SAS code. For this example, the covariance for IRSEX=0 between YEAR=1 and YEAR=2, would be B03 from ROWNUM2 or B02 from ROWNUM3. These two values would be the same in this case. The needed covariances are kept in the SAS code shown in Exhibit A.16.

The three SAS datasets created by the following examples, one containing the covariances (Exhibit A.16) and two containing the variances (Exhibit A.18), are then merged with the output dataset from the DESCRIPT procedure that generated the tests of differences (Exhibit A.10). With the proper statistics contained in one dataset, the corresponding *p* value for the tests of differences between controlled totals can be produced using the SAS PROBT function and calculated *t* test statistic (Exhibit A.20). Interwoven with these three SAS code examples are Exhibits A.17, A.19, and A.21, which show Stata code performing the same functions.

Exhibit A.16 SAS Code Based on SUDAAN Output (Identification of Covariance Components)

```
DATA COV(KEEP=IRSEX COV1);
SET OUT.SUDCOV;
IF ROWNUM=2 THEN DO; IRSEX=0; COV1=B03; END;
ELSE IF ROWNUM=8 THEN DO; IRSEX=2; COV1=B09; END;
ELSE IF ROWNUM=5 THEN DO; IRSEX=1; COV1=B06; END;

IF ROWNUM IN (2,5,8) THEN OUTPUT;

RUN;

PROC SORT DATA=COV; BY IRSEX; RUN;
```

Exhibit A.17 Stata Code (Identification of Covariance Components)

```
local max=2*2    /*number of years*number of gender categories.
This is the total number of supops*/
local range=2    /*number of gender categories. This is the number
of subpops per year*/
local compmin='max'-'range'

gen cov1=1
local counter=1
forvalues i=1/1 { /*number of contrasts needed to compare year=1
vs year=2*/
      local counter2=1
      forvalues j=1/2 {     /*number of gender categories*/
            local stop='counter2'+'compmin'
            replace cov1=M['j', 'stop'] if irsex=='j'
            local counter='counter'+1
            local counter2='counter2'+1
            }
      }

duplicates drop irsex cov1, force
      list irsex cov1
      keep irsex cov1
/* Save data to network*/
save ".\\cov.dta" , replace /*Need to save dataset since Stata
can only work with one at a time*/
```

The variances of the means are calculated in separate data steps shown in Exhibits A.18 and A.19. The variance is simply the square of the SE of the mean. The SEs of the means were output in the original procedure that generated the estimates (DESCRIPT for the SUDAAN/SAS example and svy: mean for the Stata example; see Exhibits A.1 and A.2).

Exhibit A.18 SAS Code Based on SUDAAN Output (Calculation of Variances)

```
DATA EST1(KEEP=WSUM1 VAR1 YEAR IRSEX);
SET OUT.SUDFILE;
WHERE YEAR=1;
WSUM1=WSUM;
VAR1=SEMEAN**2; /*THE variance is the SEMEAN squared*/
RUN;

DATA EST2(KEEP=WSUM2 VAR2 YEAR IRSEX);
SET OUT.SUDFILE;
WHERE YEAR=2;
WSUM2=WSUM;
VAR2 = SEMEAN**2;
RUN;
```

Exhibit A.19 Stata Code (Calculation of Variances)

```
/*Run code from Exhibit A.2 or save the output from that exhibit
into a dataset then read in that dataset here then run the
remaining code.*/
/*Note: The remaining code for this exhibit will need to be run as
a block to avoid errors.*/
preserve /*keep dataset in memory*/


keep if year ==1
gen wsum1 = wsum
gen var1 = semean^2
keep wsum1 var1 year irsex

duplicates drop year irsex, force /*keep one record per
subpopulation of interest*/

save ".\\est1.dta" , replace /*Need to save dataset since Stata
could only work with one at a time*/

restore, preserve /*restore dataset back to normal and edit for
second dataset*/


keep if year==2
gen wsum2 = wsum
gen var2 = semean^2
keep wsum2 var2 year irsex

duplicates drop year irsex, force /*keep one record per
subpopulation of interest*/

save ".\\est2.dta" , replace /*Need to save dataset since Stata
could only work with one dataset at a time*/

restore, preserve
```

Exhibit A.20 SAS Code Based on SUDAAN Output (Calculation of the *P* Value for the Test of Differences between Totals for Controlled Domains)

```
DATA P_VALUE;
MERGE EST1 EST2 OUT.SUDTESTS COV;
BY IRSEX;

PVALT=2*(1-PROBT(ABS(TOTAL/SQRT(WSUM1**2*VAR1+WSUM2**2*VAR2-
      2*WSUM1*WSUM2*COV1)),750));
RUN;
```

Exhibit A.21 Stata Code (Calculation of the *P* Value for the Test of Differences between Totals for Controlled Domains)

```
/*Run code from Exhibits A.11, A.17, and A.19 then run the
remaining code to calculate the p values*/

keep irsex total_out

*merge by irsex for dataset est1 est2 cov
merge m:m irsex using ".\\est1.dta", generate(_merge1)
merge m:m irsex using ".\\est2.dta", generate(_merge2)
merge m:m irsex using ".\\cov.dta", generate(_merge3)
generate pvalt = tprob(750,abs(total_out ///
/sqrt(wsum1^2*var1+wsum2^2*var2-2*wsum1*wsum2*cov1))) /*
 two-tail*/

drop _merge1 _merge2 _merge3
list irsex year wsum1 var1 wsum2 var2 cov1 pvalt
```

Recoding and Missing Values

In the example in Exhibits A.22 (using SAS and SUDAAN) and A.23 (using Stata), the mean age of first use of marijuana will be calculated in two ways within each exhibit. Respondents who have never used marijuana are assigned IRMJAGE=991, and if this level is included in the analysis, then the mean age calculated will be too high. Thus, two methods are shown on how to omit this level in calculating mean age of first use of marijuana using SAS and SUDAAN or Stata.

Exhibit A.22 SAS Code (Recoding a Variable) and SUDAAN DESCRIPT Procedure (Estimate Generation with (1) Missing Values and (2) Using Subpopulation)

```
/* Method 1, recoding unused values to missing*/

DATA DATANAME;
SET DATANAME;
IF IRMJAGE=991 THEN IRMJAGE_R=.;
ELSE IRMJAGE_R=IRMJAGE;
RUN;

PROC DESCRIPT DATA=DATANAME DDF=750 DESIGN=WR FILETYPE=SAS DEFT4;
NEST VESTR VEREP;
WEIGHT ANALWT;  /*Standard single-year, person-level analysis
weight*/
VAR IRMJAGE_R;  /*Marijuana Age of First Use recoded analysis
variable*/
SUBGROUP IRSEX;
/*Gender variable, where male=1 & female=2*/
LEVELS 2;
TABLES IRSEX; /*Gender*/
```

Exhibit A.22 SAS Code (Recoding a Variable) and SUDAAN DESCRIPT Procedure (Estimate Generation with (1) Missing Values and (2) Using Subpopulation) (continued)

```
PRINT MEAN SEMEAN / REPLACE STYLE=NCHS;
TITLE "ESTIMATES OF AGE OF FIRST USE OF MARIJUANA BY GENDER";
RUN;

/* Method 2, using subpopulation to omit the unused values*/

PROC DESCRIPT DATA=DATANAME DDF=750 DESIGN=WR FILETYPE=SAS DEFT4;
NEST VESTR VEREP;
WEIGHT ANALWT;  /*Standard single-year, person-level analysis
weight*/
SUBPOPN MRJFLAG=1; /*Sub setting to omit those respondents who
had never used marijuana, i.e., omitting respondents where
IRMJAGE=991*/
VAR IRMJAGE;  /*Marijuana Age of First Use analysis variable*/
SUBGROUP IRSEX;
     /*Gender variable, where male=1 & female=2*/
LEVELS 2;
TABLES IRSEX; /*Gender*/
PRINT MEAN SEMEAN / REPLACE STYLE=NCHS;
TITLE "ESTIMATES OF AGE OF FIRST USE OF MARIJUANA BY GENDER";
RUN;
```

Exhibit A.23 Stata Code (Recoding a Variable, Estimate Generation with (1) Missing Values and (2) Using Subpopulation)

```
/*Read in data*/
use using ".\\dataname.dta", clear
/*Ensure all variables are lower case*/
rename *, lower

generate irmjage_r = irmjage
replace irmjage_r =. if irmjage == 991
/*Method 1, recoding unused values to missing*/
svyset verep [pweight=analwt], strata(vestr) dof(750)
svy: mean irmjage_r, over(irsex)
/*marijuana age of first use analysis variable, gender variable*/

/*Method 2, using subpopulation to omit the unused values*/
svyset verep [pweight=analwt], strata(vestr) dof(750)
svy, subpop(mrjflag): mean irmjage, over(irsex)
```

Confidence Intervals

As discussed in Section 8 of this report, confidence intervals can be calculated using means (MEAN) and SEs (SEMEAN) from PROC DESCRIPT in SUDAAN or svy: mean in Stata. After the means and SEs are obtained (Exhibits A.1 and A.2), the code in Exhibits A.24 and A.25 can be used to create the 95 percent confidence intervals for means and totals.

Exhibit A.24 SAS Code Based on SUDAAN Output (Calculating a 95 Percent Confidence Interval)

```
DATA CI;
SET OUT.SUDFILE; /*output data from Exhibit A.1*/
T_QNTILE=TINV(0.975,750); /*define t-statistic*/
NUMBER=SEMEAN/(MEAN*(1-MEAN));
L=LOG(MEAN/(1-MEAN));

A=L-T_QNTILE*NUMBER;
B=L+T_QNTILE*NUMBER;

PLOWER=1/(1+EXP(-A));
PUPPER=1/(1+EXP(-B));
/*PLOWER AND PUPPER ARE THE 95% CIS ASSOCIATED WITH MEAN FROM
SUDAAN*/
TLOWER=WSUM*PLOWER;
TUPPER=WSUM*PUPPER;
/*TLOWER AND TUPPER ARE THE 95% CIS ASSOCIATED WITH TOTAL FROM
SUDAAN*/
RUN;
```

Exhibit A.25 Stata Code (Calculating a 95 Percent Confidence Interval for a Mean)

```
/*Run code from Exhibit A.2 or save output dataset from
Exhibit A.2 and use that as input to this code.*/
generate t_qntile = invt(750,0.975)
generate number = semean/(mean_out*(1-mean_out))
generate l=log(mean_out/(1-mean_out))
generate a = l-t_qntile*number
generate b = l+t_qntile*number
generate plower = 1/(1+exp(-a))
generate pupper = 1/(1+exp(-b))

/*plower and pupper are the 95% CIs associated with mean_out from
Stata*/

generate tlower = wsum*plower
generate tupper = wsum*pupper

/*tlower and tupper are the 95% CIs associated with total_out
from Stata*/

duplicates drop year irsex, force /*keep one record per
subpopulation of interest*/
```

Exhibit A.25 Stata Code (Calculating a 95 Percent Confidence Interval for a Mean) (continued)

```
keep year irsex nsum wsum mean_out semean total_out setotal
///t_qntile number l a b plower pupper tlower tupper
```

Calculating Percentages for Categories

Exhibits A.26 and A.27 demonstrate how to compute estimates corresponding to levels of a categorical variable. This example uses the number of days used marijuana in the past month among past month marijuana users. The variable that will be analyzed (MRJDAYS) is a categorical variable with days grouped into four levels (1=1-2 days, 2=3-5 days, 3=6-19 days, 4=20+ days). Because SUDAAN now needs to estimate percentages and SEs for each level of the variable instead of computing only one estimate for the variable overall, the CATLEVEL statement is introduced, and the PERCENT and SEPERCENT keywords replace the MEAN and SEMEAN keywords. Note that the suppression rule for percentages is the same as the suppression rule for means shown in Exhibit A.7, except PERCENT and SEPERCENT have to be divided by 100 (and thus are equivalent to MEAN and SEMEAN in the formulas). In Stata, the output will be proportions that can be directly used in the suppression rule formulas. However, if for reporting purposes, percentages need to be shown, then these proportions would need to be multiplied by 100.

Exhibit A.26 SUDAAN DESCRIPT Procedure (Frequency of Use; i.e., Number of Days Used Substance in the Past Month among Past Month Users)

```
PROC DESCRIPT DATA=DATANAME DDF=750 DESIGN=WR FILETYPE=SAS DEFT4;
NEST VESTR VEREP;
WEIGHT ANALWT;  /*Standard single-year, person-level analysis
weight*/
VAR MRJMDAYS MRJMDAYS MRJMDAYS MRJMDAYS;  /*Marijuana Use frequency
in the past month variable: 1=1-2 days, 2=3-5 days, 3=6-19 days,
4=20+ days, 5=did not use in the past month*/
CATLEVEL 1 2 3 4; /*levels of MRJMDAYS to be shown in table*/
SUBGROUP MRJMON;
/*Past month marijuana use variable, where used in past month=1 &
   did not use in past month=0*/
LEVELS 1;
TABLES MRJMON; /*Tables will show percents among marijuana users*/
PRINT WSUM NSUM PERCENT SEPERCENT TOTAL SETOTAL / REPLACE
STYLE=NCHS;
OUTPUT WSUM PERCENT SEPERCENT TOTAL SETOTAL NSUM / REPLACE
FILENAME="OUT.SUDFILE_FREQ";
TITLE "FREQUENCY OF MARIJUANA USE BY PAST MONTH MARIJUANA USERS";
RUN;
```

Exhibit A.27 Stata Code (Frequency of Use; i.e., Number of Days Used Substance in the Past Month among Past Month Users)

```
use using ".\\dataname.dta", clear
/*Ensure all variables are lower case*/
rename *, lower

svyset verep [pw=analwt], strata(vestr) dof(750)
svy: proportion mrjmdays, subpop(mrjmon)
/*This code will produce output showing proportions for marijuana
use frequency in the past month, to get percentages, these proportions
would need to be multiplied by 100*/
```

Testing Between Overlapping Domains

In addition to testing between-year differences shown in Exhibits A.10 and A.11, Exhibits A.28 and A.29 demonstrate testing between two overlapping domains. Specifically, these exhibits show how to use a stacked dataset to test whether past month cigarette use among the full population aged 18 or older is different from cigarette use among people aged 18 or older who are employed full time.

This code will apply when one domain is completely contained in another or when there is only partial overlap. The example below uses two domains, where one domain is completely contained in the other (i.e., comparing full-time employed adults to all adults—the employed group is completely contained by the all adults group). Note that the correlations between the two estimates are accounted for in this test (i.e., correlation between past month cigarette use among people aged 18 or older and past month cigarette use among people aged 18 or older employed full time).

Exhibit A.28 SAS Code (Stacking a Dataset) and SUDAAN DESCRIPT Procedure (Test of Difference when Two Groups Overlap Using Stacked Data)

```
DATA STACKED;
SET DATANAME(IN=A) DATANAME(IN=B); /*reading in data twice*/
IF A THEN DO;
  INDIC=1;
  IF EMPSTAT4 IN (1,2,3,4) THEN EMPLOY=1;
  /*EMPSTAT4 is a four-level employment variable for adults,
  where level 1 is those employed full time, 2 is those employed
  part time, 3 are those unemployed, and 4 are all other adults.
  Respondents aged 12 to 17 are coded as level 99*/
  ELSE EMPLOY=0;
END;
ELSE IF B THEN DO;
  INDIC=2;
  IF EMPSTAT4=1 THEN EMPLOY=1;
  ELSE EMPLOY=0;
END;
/*create an indicator variable for the stacked data, this will be
used in the diffvar statement in PROC DESCRIPT
```

Exhibit A.28 SAS Code (Stacking a Dataset) and SUDAAN DESCRIPT Procedure (Test of Difference when Two Groups Overlap Using Stacked Data) (continued)

```
When indic=1, employ=1 represents the full population
When indic=2, employ=1 represents those employed full time*/
RUN;

PROC SORT DATA=STACKED;
BY VESTR VEREP;
RUN;
PROC DESCRIPT DATA=STACKED DDF=750 DESIGN=WR FILETYPE=SAS;
NEST VESTR VEREP;
WEIGHT ANALWT;
VAR CIGMON;
SUBGROUP INDIC;
LEVELS 2
DIFFVAR INDIC=(1 2); /*Since subsetting in the next line to
employ=1, this is testing all persons 18+ vs. employed persons
18+*/
SUBPOPN CATAG18=1 AND EMPLOY=1;
PRINT WSUM NSUM MEAN SEMEAN TOTAL SETOTAL T_MEAN P_MEAN /
  REPLACE STYLE=NCHS;
OUTPUT WSUM MEAN SEMEAN TOTAL SETOTAL NSUM T_MEAN P_MEAN /
   REPLACE
   NSUMFMT=F8.0 WSUMFMT=F12.0 MEANFMT=F15.10 SEMEANFMT=F15.10
   TOTALFMT=F12.0 SETOTALFMT=F12.0 FILENAME="OUT.SUDTESTS";
TITLE "TESTS OF DIFFERENCES BETWEEN ALL PERSONS 18 OR OLDER AND
EMPLOYED PERSONS 18 OR OLDER";
RUN;
```

Exhibit A.29 Stata Code (Test of Difference when Two Groups Overlap Using Stacked Data)

```
/*Creating the first dataset*/
/*Read in data */
use using ".\\dataname.dta", clear
/*Ensure all variables are lower case*/
rename *, lower

gen indic = 1
gen employ = 0
replace employ = 1 if inlist(empstat4,1,2,3,4)
/*Save the dataset*/
save ".\\a26_a.dta" , replace /*Need to save dataset since Stata
can only work with one at a time*/

/*Creating the second dataset*/
/*Read in data a second time*/
use using ".\\dataname.dta", clear
/*Ensure all variables are lower case*/
rename *, lower
```

Exhibit A.29 Stata Code (Test of Difference when Two Groups Overlap Using Stacked Data) (continued)

```
gen indic = 2
gen employ = 0
replace employ = 1 if inlist(empstat4,1)
*Save the dataset
save ".\\a26_b.dta" , replace /*Need to save dataset since Stata
could only work with one at a time*/

/*Need to stack the dataset together */
use using ".\\a26_a.dta", clear
append using ".\\a26_b.dta"

/*Create the subpopulation variable*/
generate subpop = 1 if catag18 == 1 & employ == 1
svyset verep [pweight=analwt], strata(vestr) dof(750)
svy, subpop(subpop): mean cigmon, over(indic)
test [cigmon]1 = [cigmon]2
/*Since subsetting to employ=1, this is testing all persons 18+
vs. employed persons 18+ for past month cigarette use*/
/* employ is defined earlier in this exhibit and catag18=1 for
persons 18 or older and 0 otherwise  */
```

Testing Independence of Two Variables when One Variable Has Three or More Levels

When comparing population subgroups defined by three or more levels of a categorical variable, log-linear chi-square tests of independence of the subgroup and the prevalence variables are conducted first to control the error level for multiple comparisons (i.e., if the goal is to compare cigarette use among several levels of employment, first test whether cigarette use is associated with employment). Exhibits A.30 and A.31 show the code for calculating the Wald *F* test to determine whether cigarette use is associated with employment status. If Shah's Wald *F* test (transformed from the standard Wald chi-square) indicated overall significant differences, the significance of each particular pairwise comparison of interest can be tested using the SUDAAN procedure DESCRIPT (as shown in Exhibit A.28) or Stata (Exhibit A.29). The additional pairwise testing can determine which levels of employment status show significant differences in cigarette use compared with other levels of employment.

Exhibit A.30 SUDAAN CROSSTAB Procedure (Test for Independence Based on a Log-Linear Model)

```
PROC CROSSTAB DATA=DATANAME DDF=750 DESIGN=WR FILETYPE=SAS DEFT4;
NEST VESTR VEREP;
WEIGHT ANALWT;
CLASS CIGMON;
SUBGROUP EMPSTAT4; /*four level employment status variable*/
LEVELS  4;
TABLES EMPSTAT4*CIGMON;
TEST LLCHISQ / WALDF;  /*log linear hypothesis test, wald F test
statistic, if test statistic is significant, then reject null
hypothesis of no interaction*/
```

Exhibit A.30 SUDAAN CROSSTAB Procedure (Test for Independence Based on a Log-Linear Model) (continued)

```
SETENV DECWIDTH=4 COLWIDTH=15;
PRINT NSUM WSUM TOTPER ROWPER COLPER STESTVAL SPVAL SDF /
  REPLACE STYLE=NCHS;
OUTPUT STESTVAL SPVAL SDF / REPLACE FILENAME="TEST_CHI";
RUN;
```

Exhibit A.31 Stata Code (Test for Independence Based on a Log-Linear Model)

```
use using ".\\dataname.dta", clear
/*Ensure all variables are lower case*/
rename *, lower

/*Need to subset to just 4 levels of empstat4*/
generate subpop = 1 if inlist(empstat4,1,2,3,4)
/*four level employment status variable*/

svyset verep [pw=analwt], strata(vestr) dof(750)

svy, subpop(subpop): tab cigmon empstat4, llwald noadjust

/*This will give you both the adjusted and non-adjusted Wald F,
the non-adjusted test statistic will match SUDAAN*/
```

Exhibit A.32 SUDAAN DESCRIPT Procedure (Pairwise Testing)

```
PROC DESCRIPT DATA=DATANAME DDF=750 DESIGN=WR FILETYPE=SAS;
NEST VESTR VEREP;
WEIGHT ANALWT;
VAR CIGMON;
SUBGROUP EMPSTAT4;
LEVELS 4;
PAIRWISE EMPSTAT4 / NAME="Tests of differences for all levels";
PRINT WSUM NSUM MEAN SEMEAN TOTAL SETOTAL T_MEAN P_MEAN /
  REPLACE STYLE=NCHS;
OUTPUT WSUM MEAN SEMEAN TOTAL SETOTAL NSUM T_MEAN P_MEAN /
   REPLACE
   NSUMFMT=F8.0 WSUMFMT=F12.0 MEANFMT=F15.10 SEMEANFMT=F15.10
   TOTALFMT=F12.0 SETOTALFMT=F12.0 FILENAME="OUT.SUDTESTS";
TITLE "TESTS OF DIFFERENCES IN PAST MONTH CIGARETTE USE AMONG ALL
LEVELS OF EMPLOYMENT STATUS";
RUN;
```

Exhibit A.33 Stata Code (Pairwise Testing)

```
use using ".\\dataname.dta", clear
/*Ensure all variables are lower case*/
rename *, lower

/*Need to subset to just 4 levels of empstat4*/
generate subpop = 1 if inlist(empstat4,1,2,3,4)
/*four level employment status variable*/

svyset verep [pw=analwt], strata(vestr) dof(750)

/*Estimated means of past month cigarette use by employment
status*/
svy: mean cigmon, over(empstat4)
matrix Me = e(b)

local max=4 /*number of empstat4 categories*/
matrix output = J(6,7,.) /*empty matrix to store results - the
number of rows should match the number of contrasts needed*/

local counter1 = 'max' - 1
local counter2 = 'max' - 1
local contrast = 0

forvalues i=1/'counter1' {
 local stop = 'max' - 'i' + 1
 forvalues j=1/'counter2' {
  local contrast = 'contrast' + 1
  test [cigmon]'j' = [cigmon]'stop', nosvyadjust ///
   matvlc(mtest'contrast')
  matrix output['contrast', 1] = 'j'
  matrix output['contrast', 2] = 'stop'
  matrix output['contrast',7]=r(p)
  matrix output['contrast',4]=sqrt((mtest'contrast'[1,1]))
  matrix output['contrast',3]=Me[1,'j']-Me[1,'stop']
 }
 local counter2 = 'counter2' - 1
}

/*Estimated Totals*/
svy: total cigmon, over(empstat4)

matrix M = e(b) /*Store total estimates in matrix M*/
local max=4 /*number of categories*/

local counter1 = 'max' - 1
local counter2 = 'max' - 1
local contrast = 0
```

Exhibit A.33 Stata Code (Pairwise Testing) (continued)

```
forvalues i=1/'counter1' {
 local stop = 'max' - 'i' + 1
 forvalues j=1/'counter2' {
  local contrast = 'contrast' + 1
  test [cigmon]'j' = [cigmon]'stop', nosvyadjust ///
   matvlc(test'contrast')
  matrix output['contrast',6]=sqrt((test'contrast'[1,1]))
  matrix output['contrast',5]=M[1,'j']-M[1,'stop']
 }
 local counter2 = 'counter2' - 1
}
matrix colnames output = level1 level2 mean semean total_out ///
 setotal mean_pval
matrix list output
```

Testing of Linear Trends

As users, it can also be useful to test the linear trend for all data points, across all years of interest. The linear trend test can inform users about whether prevalence use has decreased, increased, or remained steady over the entire span of the years of interest. This type of test can be done using SUDAAN (as shown in Exhibits A.34 and A.36) or Stata (Exhibits A.35 and A.37). This linear trend test can be performed using a *t* test (Exhibits A.34 and A.35) or modeling (Exhibits A.36 and A.37), depending on the analysis.

Contrast Method

The *t* test method for testing linear trends is more simplistic and better suited for large-scale table production similar to that used in the detailed tables if the primary purpose is to test whether any observed differences across years are significant without consideration of other covariates. This method is also consistent with the method used in the detailed tables to test means between years and between demographic levels as shown in Exhibits A.10 and A.11. In SUDAAN, the t test method would be implemented using the CONTRAST statement in the DESCRIPT procedure as shown in Exhibit A.34. The corresponding Stata code using test statements is shown in Exhibit A.35. Both approaches are based on orthogonal polynomial coefficients. The code in Exhibits A.34 and A.35 includes two placeholders that need to be specified by the user. For each year of data, the user wants to include in the test, an additional contrast is required to account for that year. Certain variables are available for only a subgroup of NSDUH years, and sometimes the analysis of interest involves only a subgroup of years. For this reason, Table A.4 is provided to help users specify the needed information for linear trend tests involving from 3 to 15 years of data. Recall that 2 years of data would be the same as the comparison shown in Exhibits A.10 and A.11. Thus, Exhibits A.34 and A.35 are for tests across a combination of 3 or more years of data.

Table A.4 Contrast Statements for Exhibits A.34 and A.35

Number of Years (X)	Contrast Statement (Y)
15	(-7 -6 -5 -4 -3 -2 -1 0 1 2 3 4 5 6 7)
14	(-13 -11 -9 -7 -5 -3 -1 1 3 5 7 9 11 13)
13	(-6 -5 -4 -3 -2 -1 0 1 2 3 4 5 6)
12	(-11 -9 -7 -5 -3 -1 1 3 5 7 9 11)
11	(-5 -4 -3 -2 -1 0 1 2 3 4 5)
10	(-9 -7 -5 -3 -1 1 3 5 7 9)
9	(-4 -3 -2 -1 0 1 2 3 4)
8	(-7 -5 -3 -1 1 3 5 7)
7	(-3 -2 -1 0 1 2 3)
6	(-5 -3 -1 1 3 5)
5	(-2 -1 0 1 2)
4	(-3 -1 1 3)
3	(-1 0 1)

NOTE: Replace the placeholders (X) and (Y) in Exhibits A.34 and A.35 per the information in this table. Replace (X) with the numbers of years included in the linear trend test and (Y) with the corresponding contrast statement.

Exhibit A.34 SUDAAN DESCRIPT Procedure (Test of Linear Trends with DESCRIPT)

```
PROC DESCRIPT DATA=DATANAME DDF=750 DESIGN=WR FILETYPE=SAS;
NEST VESTR VEREP;
WEIGHT ANALWT;
VAR ALCMON;
SUBGROUP YEAR IRSEX;
LEVELS X 2; /*define X as the # of years*/
TABLES IRSEX;
CONTRAST YEAR = Y / NAME="LINEAR TREND TEST"; /*define Y as the
coefficients according to the number of years see Table A.4*/
PRINT WSUM NSUM MEAN SEMEAN TOTAL SETOTAL T_MEAN P_MEAN /
  REPLACE STYLE=NCHS;
OUTPUT WSUM MEAN SEMEAN TOTAL SETOTAL NSUM T_MEAN P_MEAN /
    REPLACE
    NSUMFMT=F8.0 WSUMFMT=F12.0 MEANFMT=F15.10 SEMEANFMT=F15.10
    TOTALFMT=F12.0 SETOTALFMT=F12.0 FILENAME="OUT.SUDTESTS";
TITLE "TEST OF LINEAR TREND IN PAST MONTH ALCOHOL USE BY GENDER";
RUN;
```

Exhibit A.35 Stata Code (Test of Linear Trends with TEST Statements)

```
use using ".\\dataname.dta", clear
/*Ensure all variables are lower case*/
rename *, lower

svyset verep [pw=analwt], strata(vestr) dof(750)

svy: mean alcmon, over(year irsex)
matrix Me = e(b)

matrix coeff = (Y) /*define Y as the coefficients according to
the # of years see Table A.4*/
local max=X*2 /*total number of subpops - # of years(X)*# levels
of irsex(2)*/
local counter1 = 2 /*number of categories, i.e. number of levels
of irsex*/

generate pmean=.
generate mean=.
generate semean=.
forvalues i=1/'counter1' {  /*number of categories, i.e. number
of levels of irsex*/
 local stop = 'max' / 'counter1'
 local test
 local mean
 forvalues j=1/'stop' { /*stop should be equal to the # of
coefficients defined in coeff*/
  local sub = 'i' + 'counter1'*('j'-1)
  local co = coeff[1,'j']
  local test = "'test' ('co')*[alcmon]_subpop_'sub'"
  local mean = "'mean' 'co'*Me[1,'sub']"
  if ('j' < 'stop') {
    local test = "'test' + "
    local mean = "'mean' + "
     }
 }
 test'test' = 0, nosvyadjust matvlc(mtest'counter')
 replace pmean=r(p) if irsex=='i'
 replace semean = sqrt((mtest'counter'[1,1])) if irsex=='i'
 replace mean = 'mean' if irsex=='i'
}

/*Estimated Totals*/

svy: total alcmon, over(year irsex)
matrix M = e(b)

generate total_out=.
generate setotal=.
local counter=1
```

Exhibit A.35 Stata Code (Test of Linear Trends with TEST Statements) (continued)

```
forvalues i=1/'counter1' {  /*number of categories, i.e. number
of levels of irsex*/
 local stop = 'max' / 'counter1'
 local test
 local total
 forvalues j=1/'stop' { /*stop should be equal to the # of
coefficients defined in coeff*/
  local sub = 'i' + 'counter1'*('j'-1)
  local co = coeff[1,'j']
  local test = "'test' ('co')*[alcmon]_subpop_'sub'"
  local total = "'total' 'co'*M[1,'sub']"
      if ('j' < 'stop') {
       local test = "'test' + "
      local total = "'total' + "
      }
 }
 test 'test' = 0, nosvyadjust matvlc(test'counter')
 replace setotal= sqrt((test'counter'[1,1])) if irsex=='i'
 replace total_out='total' if irsex=='i' /*Calculating the
difference between the totals of the subpopulation*/
local counter = 'counter'+1
}

/*Keeping variables that matches SUDAAN*/
keep irsex mean semean total_out setotal pmean
duplicates drop irsex mean semean total_out setotal pmean, force
/*keep one record per contrast*/

drop if total_out ==. /* drop the rows where there is no
information */
format pmean %-15.10f
format total_out %-12.0fc
format setotal %-12.0fc

/* Output the dataset*/
list irsex mean semean total_out setotal pmean
```

Modeling Method

The model-based method is more complex and flexible. This method, which was used in the analyses for the 2014 redesign impact assessment report (RIAR) (CBHSQ, 2015e) and the 2015 RIAR (CBHSQ, 2017e), can measure a change in a variable over time while controlling for covariates. The modeling method can be used for more specific tests, such as controlling for the linear year trend across years to determine a break in trend for the current year. In the examples below, the variable YEAR should be defined as a continuous variable (i.e., 1 to X with X being the number of years included in the test), and the variable YEARIND should be defined as a categorical variable (i.e., 1 if in current year of interest or 2 if not in current year of interest). The SUDAAN modeling method shown in Exhibit A.36 uses the procedure RLOGIST for logistic

regression, and the Stata modeling example shown in Exhibit A.37 uses the svy: logit command for logistic regression.

The models shown below were used to determine change, but a simpler model could be run to test overall trend across years similar to Exhibits A.36 and A.37 by removing the YEARIND variable from the code below. Note that the simplified modeling method may give a slightly different result than the DESCRIPT method under similar settings.

Exhibit A.36 SUDAAN RLOGIST Procedure (Modeling Test of Linear Trends)

```
Note: The example input dataset includes 2002-2014 NSDUH data, so YEAR
= 1 to 13 and YEARIND = 1 if in 2014 and YEARIND = 2 if not in 2014.

/*Overall model, no subpopulations*/

PROC RLOGIST DATA=DATANAME DDF=750 DESIGN=WR FILETYPE=SAS;
NEST VESTR VEREP;
WEIGHT ANALWT;
REFLEVEL YEARIND=2; /*Not in Current Year is Reference Level*/
SUBGROUP YEARIND;
LEVELS 2;
MODEL ALCMON=YEARIND YEAR; /*Model controlling for linear trend of
year to determine change in the current year*/
SETENV DECWIDTH=6 COLWIDTH=18;
PRINT BETA="BETA" SEBETA="STDERR" DEFT="DESIGN EFFECT"
T_BETA="T:BETA=0" P_BETA="P-VALUE"/ RISK=ALL TESTS=DEFAULT
T_BETAFMT=F8.2 WALDCHIFMT=f6.2 ORFMT=f10.2 LOWORFMT=f10.2
UPORFMT=f10.2 DFFMT=f7.0;
OUTPUT BETA SEBETA T_BETA P_BETA / REPLACE
FILENAME="OUT.MODEL_OUTPUT";
TITLE "MAIN MODEL OF ALCMON - OVERALL";
RUN;

/*model below is subset for Gender where IRSEX=1 is Males. Similar
model can be run for IRSEX=2 for Females*/

PROC RLOGIST DATA=DATANAME DDF=750 DESIGN=WR FILETYPE=SAS;
NEST VESTR VEREP;
WEIGHT ANALWT;
REFLEVEL YEARIND=2; /*Not in Current Year is Reference Level*/
SUBGROUP YEARIND;
LEVELS 2;
MODEL ALCMON=YEARIND YEAR; /*Model controlling for linear trend of
year to determine change in the current year*/
SUBPOPN IRSEX=1; /*Subset for Males*/
SETENV DECWIDTH=6 COLWIDTH=18;
PRINT BETA="BETA" SEBETA="STDERR" DEFT="DESIGN EFFECT"
T BETA="T:BETA=0" P BETA="P-VALUE"/ RISK=ALL TESTS=DEFAULT
T BETAFMT=F8.2 WALDCHIFMT=f6.2 ORFMT=f10.2 LOWORFMT=f10.2
UPORFMT=f10.2 DFFMT=f7.0;
OUTPUT BETA SEBETA T BETA P BETA / REPLACE
FILENAME="OUT.MODEL OUTPUT";
TITLE "MAIN MODEL OF ALCMON - MALES";
RUN;
```

Exhibit A.37 Stata Code (Modeling Test of Linear Trends)

```
Note: The example input dataset includes 2002-2014 NSDUH data, so YEAR
= 1 to 13 and YEARIND = 1 if in 2014 and YEARIND = 2 if not in 2014.

use using ".\\dataname.dta", clear

svyset verep [pw=analwt], strata(vestr) dof(750)

/*Overall model controlling for linear trend of year to determine
change in the current year.*/
svy: logit alcmon ib2.yearind year

/*Create a subsetting variable, irsex_1 that will be 1 for males
(IRSEX=1) and zero otherwise. A similar variable can be created to
subset for females (IRSEX=2)*/
generate irsex_1 = 0
replace irsex_1 = 1 if irsex == 1

/*Model subsetting by gender and controlling for linear trend of year
to determine change in the current year. A similar model can be run
for females(IRSEX=2).*/
svy, subpop (irsex_1): logit alcmon ib2.yearind year
```

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