Bureau of Justice Statistics Research and Development Series

Evaluation of Direct Variance Estimation, Estimate Reliability, and Confidence Intervals for the National Crime Victimization Survey

Rick Williams, PhD
David Heller, MS
Lance Couzens, BS
Bonnie Shook-Sa, MAS
Marcus Berzofsky, DrPH
Hope Smiley-McDonald, PhD
Chris Krebs, PhD
RTI International

NCJ 249242

R&DP-2015: 02
NCJ 249242
December 28, 2015

This document was prepared using Federal funds provided by the U.S. Department of Justice under Cooperative Agreement number 2011-NV-CX-K068. The BJS Project Managers were Lynn Langton, BJS Statistician, and Michael Planty, Victimization Unit Chief.

CONTENTS

LIST OF EXHIBITS

SECTION 1. DATA STRUCTURE

The National Crime Victimization Survey (NCVS), sponsored by the Bureau of Justice Statistics (BJS), estimates the incidence and describes the characteristics of criminal victimization in the United States. When calculating NCVS estimates, researchers must take into account the complex stratified, four-stage sample design and analysis weights. Stratification, clustering, and variation in analysis weights all affect the variances of survey parameters, and not appropriately accounting for these factors during estimation can lead to invalid results (Cochran, 1977).

Two broad methods exist for calculating variances of estimates from complex sample designs: generalized variance functions (GVFs) and direct variance estimation. GVFs model the design-consistent variances for multiple survey estimates to obtain GVF parameters. Using the formulas and parameters from the GVF models, users are able to calculate approximations of variances without knowledge of the sample design. Direct variance estimation uses software that accounts for complex sample designs. Two direct variance techniques are Taylor series linearization (TSL) and balanced repeated replication (BRR).

Currently, BJS uses GVFs to calculate variances of NCVS estimates. However, the GVFs developed for the NCVS do not allow for complex analyses such as regression modeling, are cumbersome when multiple estimates are produced, and produce GVF estimates for outcomes not included in developing the GVF parameters that are of unknown accuracy. Use of GVFs requires knowledge about the correct GVF parameters and formulas to use, and these decisions are dependent on the outcome of interest.

Direct variance estimation has not been used for the NCVS because two weights are needed for the calculation of key NCVS estimates (victimization rates): a population weight and a victimization weight. The population weight represents the number of persons or households in a domain of interest. The victimization weight represents the number of victimizations experienced by the person or household. To properly calculate the variance of a rate, an analyst needs both weights. However, currently, no software package allows for two weight values to be used in the calculation of the variance, making it difficult to use direct variance estimation.

This report examines the feasibility of using direct variance estimation for the NCVS. It compares GVF estimates to two direct variance estimation methods (TSL and BRR). Furthermore, it provides recommendations regarding the calculation of confidence intervals (CIs) and identification of unstable estimates. A companion user's guide has been developed to describe how to implement the direct variance techniques detailed in this report using different software packages (Shook-Sa, Couzens, & Berzofsky, 2014).

When comparing direct variance estimation to the current GVF approach, the following areas will be addressed:

1. Single-year estimation
2. Pooled-year estimation
3. Cross-single-year estimation
4. Cross-pooled-year estimation
5. Identifying estimates with low reliability
6. CIs

All comparisons will use "with-series" victimization rates and the newly available "with series" GVF parameters, as further discussed in ***Section 2.3***.

SECTION 2. VARIANCE ESTIMATION

2.1 National Crime Victimization Survey Design

As described in the NCVS codebook for 2010 (BJS, 2010), the NCVS sample consists of approximately 50,000 sample housing units selected each year with a stratified, multistage cluster design. The primary sampling units (PSUs) composing the first stage of the sample include counties, groups of counties, or large metropolitan areas. PSUs are further grouped into strata. Large PSUs are included in the sample automatically and each is assigned its own stratum. These PSUs are considered to be self-representing (SR) because all of them were selected. The remaining PSUs, called non-self-representing (NSR) because only a subset of them was selected, were combined into strata by grouping PSUs with similar geographic and demographic characteristics, as determined by the decennial census used to design the sample. A sample of one NSR PSU was selected from each stratum. For analytic purposes, the SR PSUs were each separated into two pseudo-PSUs and labeled as coming from the same pseudo-stratum. Each NSR PSU was paired with a second NSR PSU selected from a similar stratum and labeled as two pseudo-PSUs coming from the same pseudo-stratum. The pseudo-PSUs and pseudo-strata are important concepts for the variance estimation methods described below and are used to describe the sample design when analyzing the data.

The NCVS sample of PSUs is drawn every 10 years from the decennial census and used until the next decennial census is available when a new sample of PSUs is selected. At approximately mid-decade, sample selection from the most recent census is phased in; before that, sample selection is based on the census before the most recent one. For example, before 1995, the sample was drawn from the 1980 decennial census. From January 1995 until December 1997, the sample drawn from the 1990 census was phased in. From January 1998 until approximately 2005, the complete NCVS sample was drawn from the 1990 census. From 2005 through 2007, samples from the 2000 census were phased in.

Because of the continuing nature of the NCVS, a rotation scheme is used to avoid interviewing the same household indefinitely. The sample of housing units is divided into six rotation groups, and each group is interviewed every 6 months for a period of 3 years. Within each of the six rotation groups, six panels are designated. A different panel is interviewed each month during the 6-month period.

The combined process of phasing out and phasing in samples from the 1990 and 2000 censuses, along with rotation groups, is shown in ***Exhibit 2.1A***. In year 2004, the sample was derived entirely from the 1990 census. Years 2005, 2006, and 2007 were a so-called phase-in/phase-out period in which the sample included elements from both the 1990 and the 2000 censuses. This was followed by a period in which the sample was derived entirely from the 2000 census. As will be shown, the transition between decennial PSU samples is important when implementing direct variance estimation.

2.2 Variance Estimation Options

Multistage sample designs, including the design of the NCVS, complicate the analysis of the data because the individual observations are not independent (Wolter, 1985). The observations are correlated because of having been selected from geographic clusters of observations of likely related units (e.g., within PSUs or housing units). Also, using the same sample of PSUs for a 10-year period, combined with repeated interviews of the same housing units over rotating 3-year periods, causes estimates from years using the same PSU sample to be correlated.

In the sections that follow, three methods for variance estimation are discussed and compared. The first is GVFs, which have been available for use with the NCVS public use data for many years. The other two, TSL and BRR, are two direct variance estimation methods that are being explored in this report as alternative methods for use with the NCVS public use data.

Direct variance estimation methods use statistical software designed to calculate the variance of an estimate directly from the full dataset. To implement direct variance estimation, users must organize and code the data so that each observation is associated with the strata and PSU from which it was selected. To this end, the public use data files include the following two variables:

Exhibit 2.1A. Example of Sample Rotation and Phase-in and Phase-out of Decennial Samples

Form **NCVS-551**
(10-10-2000)

U.S. DEPARTMENT OF COMMERCE
BUREAU OF THE CENSUS

REDUCED NCVS ROTATION CHART

July 2004-June 2008

	1990 Sample for Continuing and Outgoing Areas (Exception noted by shading)								2000 Sample for Continuing and New Areas (Exceptions noted by shading)										
Year/Month	J21					J22			J23				J24						J25
2004 JULY	12	13	14	15	16	11	12												
AUG	22	23	24	25	26	21	22												
SEPT	32	33	34	35	36	31	32												
OCT	42	43	44	45	46	41	42												
NOV	52	53	54	55	56	51	52												
DEC	62	63	64	65	66	61	62												
2005 JAN		13	14	15	16	11	12	13					11						
FEB		23	24	25	26	21	22	23					21						
MAR		33	34	35	36	31	32	33					31						
APR		43	44	45	46	41	42	43					41						
MAY		53	54	55	56	51	52	53					51						
JUNE		63	64	65	66	61	62	63					61						
JULY			14	15	16	11	12	13					11	12					
AUG			24	25	26	21	22	23					21	22					
SEPT			34	35	36	31	32	33					31	32					
OCT			44	45	46	41	42	43					41	42					
NOV			54	55	56	51	52	53					51	52					
DEC			64	65	66	61	62	63					61	62					
2006 JAN				15	16	11	12		~~13~~	14	15	16	11	12	13				
FEB				25	26	21	22		~~23~~	24	25	26	21	22	23				
MAR				35	36	31	32		~~33~~	34	35	36	31	32	33				
APR				45	46	41	42		~~43~~	44	45	46	41	42	43				
MAY				55	56	51	52		~~53~~	54	55	56	51	52	53				
JUNE				65	66	61	62		~~63~~	64	65	66	61	62	63				
JULY					16	11	12			14	15	16	11	12	13	14			
AUG					26	21	22			24	25	26	21	22	23	24			
SEPT					36	31	32			34	35	36	31	32	33	34			
OCT					46	41	42			44	45	46	41	42	43	44			
NOV					56	51	52			54	55	56	51	52	53	54			
DEC					66	61	62			64	65	66	61	62	63	64			
2007 JAN						11	12				15	16	11	12	13	14	15		
FEB						21	22				25	26	21	22	23	24	25		
MAR						31	32				35	36	31	32	33	34	35		
APR						41	42				45	46	41	42	43	44	45		
MAY						51	52				55	56	51	52	53	54	55		
JUNE						61	62				65	66	61	62	63	64	65		
JULY							12					16	11	12	13	14	15	16	
AUG							22					26	21	22	23	24	25	26	
SEPT							32					36	31	32	33	34	35	36	
OCT							42					46	41	42	43	44	45	46	
NOV							52					56	51	52	53	54	55	56	
DEC							62					66	61	62	63	64	65	66	
2008 JAN	Phase-in Complete												11	12	13	14	15	16	11
FEB													21	22	23	24	25	26	21
MAR													31	32	33	34	35	36	31
APR													41	42	43	44	45	46	41
MAY													51	52	53	54	55	56	51
JUNE													61	62	63	64	65	66	61

1990 Sample in outgoing areas only

Phase-in Begins

2000 Sample in continuing areas only

Rotation 3 was

Start of sample cut at 10%

2000 Sample in new areas only

First interview in new areas

Last interview in outgoing areas

1990 Sample in continuing areas only and start of sample cut at 25%

Pseudo-stratum (V2117): The variable designating the pseudo-stratum code associated with each observation created from the sampling strata used to select the PSUs.

Half-sample (V2118): The variable designating the pseudo-PSU code associated with each observation created from the sampling PSUs selected into the sample. The term "half-sample" is used because each pseudo-stratum includes two pseudo-PSUs that approximately divide the sample in half.

The terms "strata" and "PSU" will be used throughout this document to refer to the variables pseudo-stratum (V2117) and half-sample (V2118).

Exhibit 2.2A presents the number of strata included on the NCVS public use files from 1993 through 2011, with each stratum containing two PSUs. The exhibit also presents the grouping of years for which decennial census data were used to select the sample of PSUs contributing to the data for the years in each group. Except for issues arising from the phase-in/phase-out periods, the PSUs used to select the data within a Year Group are the same for each year, whereas for the between-Year Groups the samples of PSUs are different. Thus, the data between Year Groups are assumed to be independent, but the data within a Year Group are assumed to be cluster correlated within the PSUs across years. These assumptions will be used for direct variance estimation. Although these assumptions are only approximately true because of the phase-in/phase-out process, the assumptions are necessary because the public use data files do not contain the level of detail needed to separately account for the overlap of PSUs during the phase-in/phase-out period. The approximations will, however, support appropriate direct variance estimation.

Exhibit 2.2A. Grouping of Years by Decennial Census and Number of Strata by Year

Grouping of Years by Decennial Census	Year	Number of Strata
Year Group 1 Primary sampling unit (PSU) sample primarily from the 1980 decennial census	1993	164
	1994	164
	1995	164
	1996	164
Year Group 2 PSU sample primarily from the 1990 decennial census	1997	143
	1998	143
	1999	143
	2000	143
	2001	143
	2002	143
	2003	143
	2004	143
	2005	144
Year Group 3 PSU sample primarily from the 2000 decennial census	2006	160
	2007	160
	2008	160
	2009	160
	2010	160
	2011	160

2.2.1 Generalized Variance Functions

Within the NCVS, GVFs are formulae estimated by the U.S. Census Bureau that approximate the variance of an estimate as a function of readily available information about the estimate. The process starts by selecting a set of NCVS estimates and calculating their associated variances. Over the years, the Census Bureau has estimated the variances using different direct variance estimation methods, including TSL, jackknife, BRR, and successive difference replication. The first three methods are widely used (Wolter, 1985), but the latter is a more specialized method described in Fay and Train (1995) and Ash (2010). Modeling methods like those described in Wolter (1985, Chapter 5) are then used to model the variance as a function of such values as the estimate, the sample size or the population size, or other characteristics related to the sample design (such as location of urban or rural) or to the respondent (such as age, race, or marital status). It is also common that separate models are required for various types of estimates—for example, victimization rates, totals, or percentages. The resulting models are called GVFs.

Although GVFs are easy to use, they are limited to the specific situations for which they are designed. Moreover, separate GVFs are needed for different victimization types and for each year. Thus, when conducting a large analysis spanning several years and victimization types, many different GVFs are needed, which makes it difficult to manage the analysis.

To appropriately calculate GVF estimates, analysts must decide whether to include or exclude series or repeat victimizations. Series victimizations occur when an NCVS respondent recalls at least six criminal incidents of a similar nature but cannot recall the dates and other details of the individual incidents well enough to report them separately. In these cases, the respondent can report the number of victimizations and the details of only the most recent event. Until recently, BJS reported crime statistics *excluding* series victimizations, but BJS now reports crime victimization statistics *including* series victimizations (Lauritsen, Owens, Planty, Rand, & Truman, 2012). Up until this change, the U.S. Census Bureau created GVFs for estimates excluding series victimizations. In July 2013 and February 2014, the Census Bureau issued updated GVFs for estimates including series victimizations for years 1993–2012. Because BJS recommends including series victimizations in the calculation of victimization rates, this report will use data including series victimizations. However, because the inclusion of series victimizations dramatically affects estimated variances, if series victimizations are excluded, the appropriate “without-series” GVF parameters should be used in estimation. The importance of using the appropriate set of GVF parameters is demonstrated in Section 2.3.1.

2.2.2 Taylor Series Linearization

For a stratified multistage cluster sample like the one used for the NCVS, there is an unbiased variance estimator for a linear statistic. An example of a linear statistic is the estimated total number of victimizations for a year given by $= \sum_{j=1}^{n} w_j y_j$, where w_j and y_j are the analysis weight and the number of victimizations incurred by the j^{th} participant in the survey, respectively. The variance estimator is based on the commonly used assumption that the PSUs in a multistage sample were selected with replacement. Although replacement PSU selection is almost never done, it is a good approximating assumption when the sampling fraction (i.e., the ratio of the number of PSUs selected to the total number of PSUs in the stratum) among the PSUs is small. For the NCVS, only two PSUs per stratum are selected out of a large number of PSUs available per stratum, so the replacement PSU sampling assumption is appropriate. The variance estimation formula is

$$V_{TSL}(Y) = \sum_{h=1}^{H} \frac{n_h}{n_h - 1} \sum_{i=1}^{n_h} (Y_{hi} - \bar{Y}_h)^2,$$

where $Y_{hi} = \sum_{j=1}^{m_{hi}} w_{hij} y_{hij}$ and $\bar{Y}_h = \sum_{i=1}^{n_h} y_{hi} / n_h$. The subscripts have been expanded to include strata (h), PSUs (i), and respondents (j), and with n_h being the number of PSUs in a stratum and m_{hi} the number of respondents in a PSU. This variance estimator has been shown to be unbiased for linear statistics (Särndal, Swensson, & Wretman, 1992; Williams, 2000).

When a nonlinear statistic is being considered, the TSL method replaces the nonlinear statistic with a first-order Taylor series linear approximation and then uses the above variance estimator with the linear approximation data to estimate the variance of the nonlinear statistic. The resulting variance estimate is a consistent estimate of the variance of the nonlinear statistic. For example, the victimization rate is estimated by $R = Y/X$, where Y is the estimated total number of victimizations as just described and $X = \sum_{j=1}^{n} w_j$ is the estimated total number of people in the population. Following the descriptions in Wolter (1985, Section 6.5) or Williams (2008), it can be shown that the linearized values for a ratio are $z_j = (y_j - Rx_j)/X$.

The TSL method is widely implemented in statistical analysis software packages, such as SUDAAN, SAS, Stata, and SPSS (complex samples package). All of these analysis packages automatically determine the linearized values for a wide range of statistics without the need for user input. However, the analysis packages require the user to specify the strata and PSUs used to select the sample so that the variance can be estimated appropriately. For an estimate based upon data from a single year, the variables pseudo-stratum (V2117) and half-sample (V2118) are the variables that specify the strata and PSUs to the analysis package. The situation is slightly more complex when analyzing data across years because of the use of the same PSUs across 10-year intervals and the repeated interviewing of the same households over 3 years. In this situation, the same strata and PSUs are used across years within the Year Groups shown in ***Exhibit 2.2A***. The key is to group data across the years by the strata and PSUs used to select the data. Thus, ***Exhibit 2.2A*** illustrates how to create cross-year strata so that data within the same Year Group use the same strata and PSUs in the variance calculation, which will capture the statistical correlation among these data. On the other hand, the cross-year strata will separate the data from two different Year Groups in the variance calculation and treat the different Year

Exhibit 2.2.2A. Cross Year Strata and PSUs

Cross-Year Strata		PSUs	
Year Group	Pseudo-stratum (V2117)	Half-sample (V2118)	Years of Data
1	1	1	1993–1996
1	1	2	1993–1996
1	2	1	1993–1996
1	2	2	1993–1996
⋮	⋮	⋮	⋮
1	164	1	1993–1996
1	164	2	1993–1996
2	1	1	1997–2005
2	1	2	1997–2005
2	2	1	1997–2005
2	2	2	1997–2005
⋮	⋮	⋮	⋮
2	144	1	1997–2005
2	144	2	1997–2005
3	1	1	2006–2011
3	1	2	2006–2011
3	2	1	2006–2011
3	2	2	2006–2011
⋮	⋮	⋮	⋮
3	160	1	2006–2011
3	160	2	2006–2011

Groups as statistically independent. This process is more fully described in the User's Guide (Shook-Sa, Couzens, & Berzofsky, 2014).

2.2.3 Balance Repeated Replication

BRR is another commonly used direct variance estimate method for complex sample surveys (Lumley, 2008). Like the TSL method, BRR takes advantage of the with-replacement sampling assumption of the PSU sample. BRR is most easily implemented for a stratified sample with two PSUs selected per stratum like the pseudo-strata and pseudo-PSUs of the NCVS. The NCVS is separated into half-samples created by selecting one PSU from each stratum. The weights of observations in the selected half-sample are doubled, and the weights for the remaining observations are set to zero. A half-sample estimate of a statistic (victimization total, rate, or percent) is then obtained from the half-sample data. A large number of half-samples are generated along with a corresponding set of half-sample estimates denoted as $\theta_1, \ldots, \theta_G$, where G is the total number of half-samples created. The variance is then estimated by

$$V(\theta) = \sum_{g=1}^{G} \left(\theta_g - \theta\right)^2 / G,$$

where θ is the estimated statistic from the full NCVS sample. The set of half-samples is usually selected so that they are in full orthogonal balance, in which case an efficient and consistent estimate of the variance is obtained. The conditions and methods for creating half-samples with full orthogonal balance are described by Wolter (1985, Chapter 3).

Similar to the TSL method, special consideration is needed to account for the overlap in strata and PSUs within a Year Group. The same cross-year strata and PSUs presented in ***Exhibit 2.2A*** can be used when forming the BRR half-samples. When data from a single Year Group are analyzed, the strata and PSUs specific to that Year Group are used to form the half-samples for BRR estimation. Once formed, the same half-samples are used for all years within the Year Group. For example, Year Group 1 has 164 strata, each with two PSUs for all the years of data in Year Group 1; the half-samples would be formed from these strata and PSUs. For analyses using data from two Year Groups, half-samples are needed using the strata and PSUs from both Year Groups. For example, if data were being compared across Year Groups 1 and 2, say pooled data from 1993 through1996 compared with those from 1997 through 1999, then half-samples would be created from the combined 208 (164 + 144 = 208) strata from Year Groups 1 and 2. Finally, if all three Year Groups were included in the analysis, half-samples would be created from all 368 strata (164 + 144 + 160 = 368). In any of these cases, the data within a Year Group would be included or excluded from the same half-samples so as to capture the correlations due to sharing the same PSUs in a Year Group.

2.3 Single-Year Estimates

This section explores single-year victimization rate and total estimates and compares the GVF, TSL, and BRR variance estimation approaches. It also demonstrates why choosing the correct set of parameters (i.e., parameters including or excluding series victimizations) is essential when calculating GVF estimates. The following victimization types are included:

Personal Victimization Types

- Rape/sexual assault
- Robbery
- Aggravated assault
- Simple assault
- Personal theft

Property Victimization Types

- Household burglary
- Motor vehicle theft
- Theft

For each of these victimization types, estimates were produced for the following subpopulations:

Personal Victimization Subpopulations

- Sex
- Race
- Age category
- Region
- Rural/urban
- Metropolitan Statistical Area (MSA) status

Property Victimization Subpopulations

- Household income
- Region
- Rural/urban
- MSA status

To study the relationships among these variance estimates, the percent relative standard error (RSE) was used. The percent RSE, the square root of the variance of an estimate divided by the estimate, is expressed as a percentage $\left(100 \times \sqrt{Var(Y)}/Y\right)$. The percent RSE removes the scale of the estimate and allows comparisons to be made across multiple types of estimates with different scales (e.g., totals versus rates).

Exhibit 2.3A presents three figures summarizing the results for crime victimization rates for single-year estimates from 2001 through 2011. Series victimizations are included in the estimates and the GVFs. The figures display the relationship between the three variance estimation methods—TSL vs. GVF, BRR vs. GVF, and TSL vs. BRR—by plotting percent RSE from one method along the horizontal (x) axis and the alternative method along the vertical (y) axis. If two methods produce consistent results then the bulk of the RSE comparisons would fall along the 45° line of equality between the two methods with some estimates varying slightly above or below the line. Figures were also produced for crime victimization totals, but they were almost identical to the victimization rate figures and are therefore, not presented herein.

The first item of note is that both the TSL and the BRR methods match the GVF method well. The RSEs in both ***Figures 1*** and ***2*** of ***Exhibit 2.3A*** are centered on the 45° line, indicating congruence between the two methods. When the RSEs are less than 30%, they are tightly clustered around the 45° line, whereas a wider spread is found for the estimates with RSEs greater than 30%. An estimate with a large RSE is not reliably estimated and will have a wide CI no matter which variance estimation method is used. ***Figures 1*** and ***2*** provide confidence that the TSL and BRR methods applied to the public use data files are matching the methods used by the Census Bureau when producing the GVFs.

A second item of note is that the TSL and BRR methods yield almost exactly the same results as shown in ***Figure 3*** in ***Exhibit 2.3A***. All plotted values are extremely close to the 45° line. In addition, the relationship between TSL and BRR was explored for pooled-year estimates and for comparison tests between years. All of these situations also showed that TSL and BRR variance estimates and tests of differences were almost exactly the same for the NCVS public use data. In addition, as described in ***Section 2.2.3***, the BRR method requires a much more complex data setup than the TSL method does to account for the phase-in/phase-out of PSUs across the Year Groups. Furthermore, although several analysis packages support both TSL and BRR methods, one of the most widely used by NCVS researchers is SPSS, which does not support BRR variance estimation. For these reasons, BRR direct variance estimation was not examined further, and the remainder of this report will focus on TSL direct variance estimation.

Exhibit 2.3A. Percent RSEs for Selected Crime Victimization Rates for Single Years from 2001 through 2011

Figure 1. TSL vs. GVF

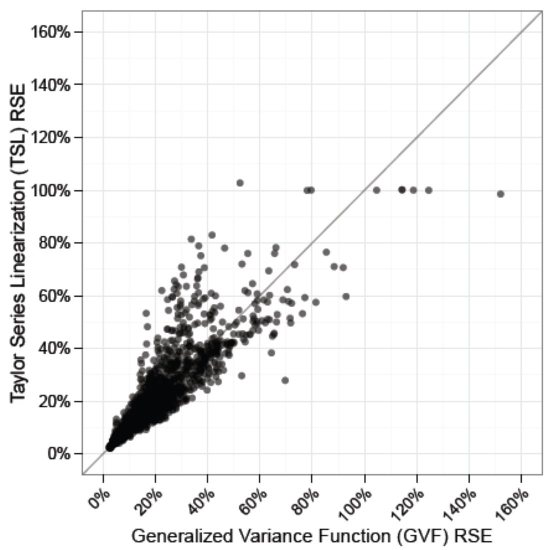


Figure 2. BRR vs. GVF

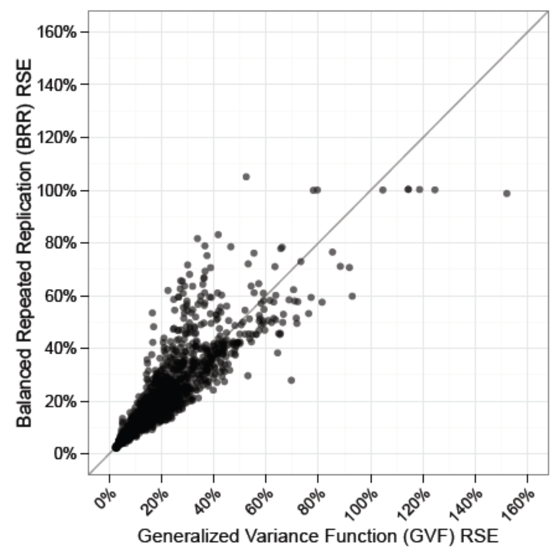
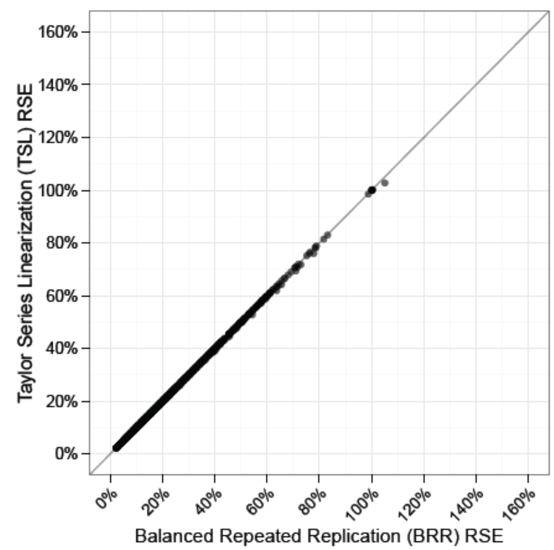


Figure 3. TSL vs. BRR



Note: Series victimizations are included in both the estimates and in the GVFs.

As stated earlier, the U.S. Census Bureau has prepared GVFs for estimates in which series victimization reports are both included and excluded, and the appropriate parameters must be used to obtain unbiased variance estimates. To demonstrate the importance of using the correct GVF parameters, single-year estimates were prepared for the years 2001 through 2011 including series victimizations. Direct TSL variances were calculated for all of these estimates. GVF estimates were calculated two ways: using the "with series" parameters (as appropriate when series victimizations were included) and using the without-series parameters. The results are summarized in ***Exhibit 2.3B***, in which the percent RSEs from the TSL method are compared with the percent RSEs from the GVFs.

Exhibit 2.3B. Percent RSEs for Selected Crime Victimization Rates for Single Years from 2001 through 2011

Figure 1. GVFs Excluding Series Victimizations

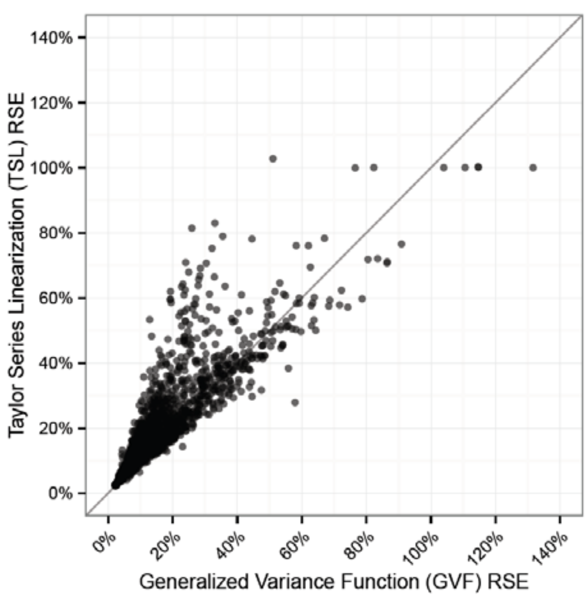
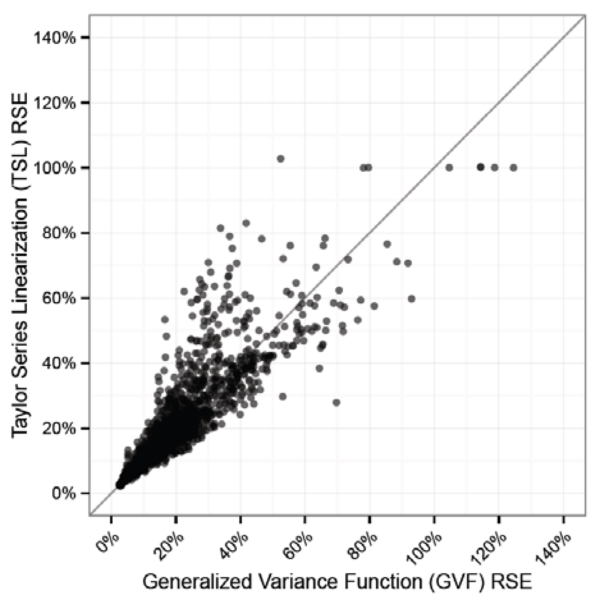


Figure 2. GVFs Including Series Victimizations



Note: Series victimizations are included in the estimates for both Figures 1 and 2.

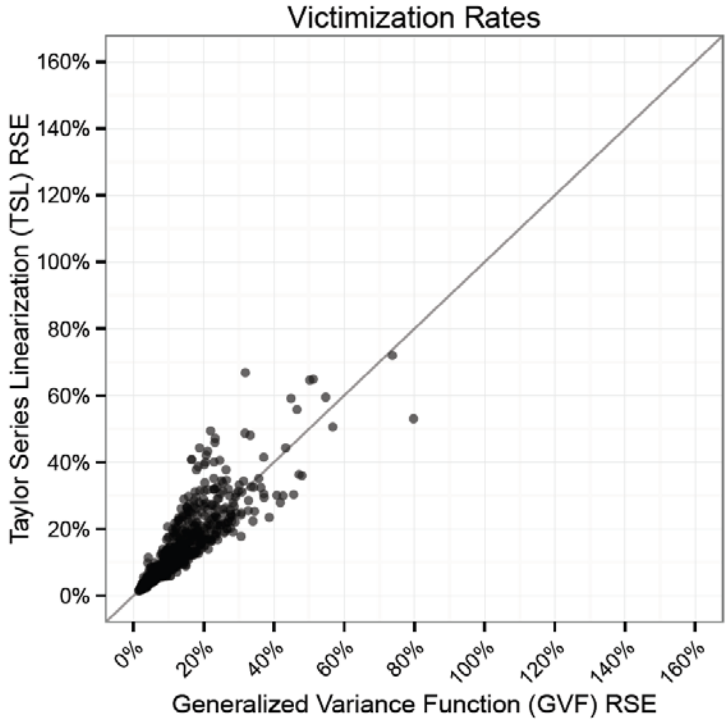
When the estimates include series victimizations but the without-series GVF parameters are used, as shown in ***Figure 1*** of ***Exhibit 2.3B***, the majority of the plotted values are above the 45° line of equality, which means that most of the TSL percent RSEs are greater than the GVF percent RSEs. This result is likely because the GVFs for these years were developed excluding series victimizations and the GVF RSEs are too small because they do not account for the added variability that arises from including series victimizations. Additional evidence for this inference is shown in ***Figure 2*** of ***Exhibit 2.3B***, in which the estimates and GVF parameters include series victimizations. In this situation, the TSL and the GVF methods closely align, as shown by the clustering of the plotted RSEs around the 45° line of equality. As with ***Exhibit 2.3A***, estimates are more tightly clustered around the 45° line when the RSEs are less than 30%, whereas a wider spread is found for the estimates with RSEs greater than 30%. This figure shows that TSL and GVF estimates track well when series victimizations are included and the appropriate GVF parameters are used. To confirm that the without-series parameters track well with direct variance estimates when series victimizations are excluded, annual victimization rates were calculated excluding series victimizations, and percent RSEs for TSL estimates were compared to percent RSEs for GVF estimates (using the without-series parameters). The results were very consistent, clustering around the 45° line (figures not included). These results provide further evidence that TSL and GVF estimates track well regardless of whether series victimizations are included or excluded, provided that the appropriate GVF parameters are used. The remainder of this report will focus solely on estimates including series victimizations and the appropriate GVF parameters.

2.4 Pooled-Year Estimates

Because many types of victimization occur at very low rates, it is often necessary to pool several years of data together in order to obtain enough cases to support an analysis. This section considers estimates from data pooled across 3-year periods for the same victimization types and subpopulations listed in ***Section 2.3***.

Exhibit 2.4A presents a comparison of the TSL percent RSEs and the GVF percent RSEs for pooled estimates from five different Year Groups: 2001–2003, 2002–2004, 2005–2007, 2008–2010, and 2009–2011 (similar to what was presented in ***Exhibit 2.3A***). The results for crime victimization totals were nearly identical to the rates and, thus, are not included. The GVF and TSL variance methods correspond closely for pooled-year estimates, as demonstrated by the plotted values, which are clustered around the 45° line of equality for the two methods. This reinforces the earlier conclusion that the TSL direct variance estimation method has been properly specified for use with the NCVS public use data.

Exhibit 2.4A. Percent Relative Standard Errors (RSEs) for Selected Crime Victimization Rates for Pooled-Year Estimates from 2001–2003, 2002–2004, 2005–2007, 2008–2010, and 2009–2011



2.5 Cross-Single-Year Comparisons

This section considers tests of differences, or comparisons, between estimates from two years. The hypothesis tested is H_o: $R_u = R_s$ vs. H_a: $R_u \neq R_s$, where R_u and R_s are the victimization rates for two different years, u and s. The test statistic is $z = |r_u - r_s| / \sqrt{Var(r_u - r_s)}$, where r_u and r_s are the estimated values of the two victimization rates being compared. The test statistic is considered to follow a standard normal distribution. Likewise, comparisons of victimization totals can also be tested by substituting totals for rates in the preceding hypothesis and test statistic. For this analysis, the same victimization types and subpopulations listed in ***Section 2.3*** were included for three sets of single-year comparisons: 2004 against 2005, 2005 against 2006, and 2001 against 2011. These comparisons include examples of years in the same Year Group drawn from the same PSUs (2004 against 2005), years spanning the phase-in/phase-out period (2005 against 2006), and years in different Year Groups consisting of independent samples of PSUs (2001 against 2011).

Exhibit 2.5A presents the p-values associated with the tests of the cross-year comparisons computed using either the TSL or the GVF method to estimate the variance of the difference between 2 years. Similar to previous exhibits, the TSL and GVF p-values are compared by plotting the GVF p-values along the horizontal (x) axis and the TSL p-values along the vertical (y) axis. For both victimization rates and totals, the p-values are well aligned along the 45° line of equality, which shows that the two methods yield similar results.

Exhibit 2.5A. P-values for Comparisons between Single-Year Victimization Estimates

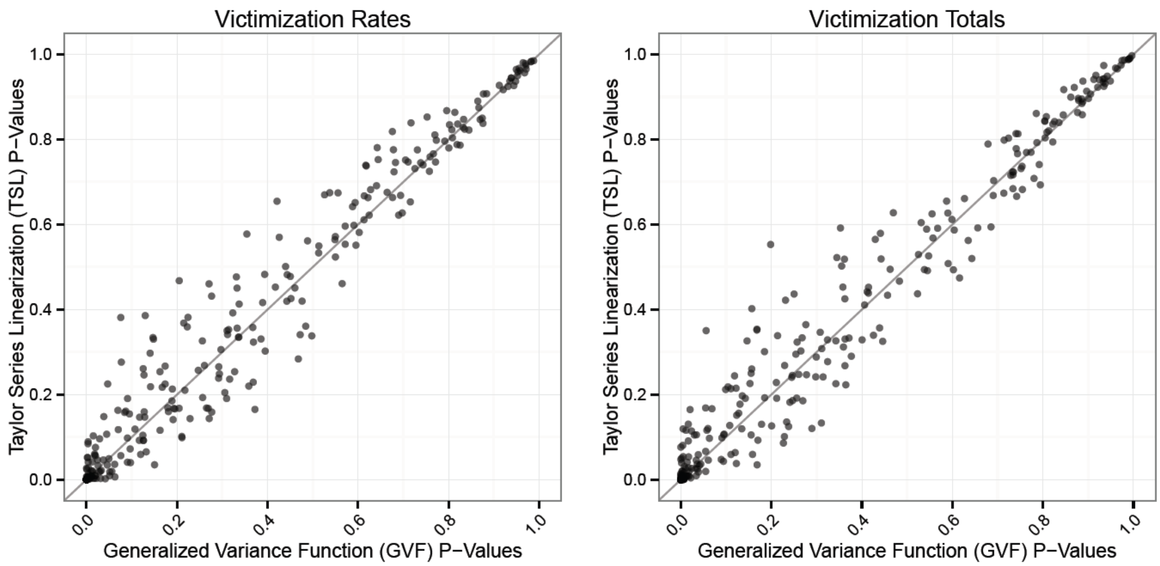
Note: Comparisons between 2004 and 2005 estimates, 2005 and 2006 estimates, and 2001 and 2011 estimates.

2.6 Cross-Pooled-Year Comparisons

As was noted in ***Section 2.4***, it is often necessary to pool several years of data together in order to obtain enough cases to support an analysis. This section extends the discussion in ***Section 2.5*** to the test of differences, or comparisons, between estimates from two different poolings of years. The same hypothesis and test statistic from ***Section 2.5*** are considered here and comparisons are made between two sets of pooled-year estimates (2002–2004 against 2005–2007 and 2001–2003 against 2009–2011) for the same victimization types and subpopulations listed in ***Section 2.3***. Like the single-year comparisons, these years were selected to span multiple Year Groups and to include years during a phase-in/phase-out period.

Exhibit 2.6A presents the p-values associated with tests of the cross-pooled-year comparisons using either the TSL or the GVF variance estimation methods in the same way as was done in ***Exhibit 2.5A***. Again, the TSL and the GVF methods yield similar results for both victimization rates and totals, with the p-values well aligned along the 45° line of equality.

Exhibit 2.6A. P-values for Comparisons between Pooled-Year Victimization Estimates



Note: Comparisons between pooled 2002–2004 estimates and pooled 2005–2007 estimates, and pooled 2001–2003 estimates and pooled 2009–2011 estimates.

SECTION 3. ESTIMATE RELIABILITY

3.1 Introduction

This section considers reliability standards for NCVS estimates and rules for flagging estimates with low reliability. In general terms, it is desirable that a NCVS estimate neither vary widely because of sampling variation nor be overly influenced by a small number of observations. When neither situation occurs, an estimate is said to be reliable because the users can have confidence that conclusions drawn from the estimate are likely not due to random chance. On the other hand, it is difficult to interpret an unreliable estimate because the observed value may be due to random chance or may not represent the target population well. It is common for large national surveys like the NCVS to provide guidance to users concerning unreliable estimates. This is often done by establishing rules for flagging estimates in reports that potentially have low reliability. This chapter presents an evaluation of such rules using the TSL variance estimation approach.

3.2 Potential Reliability Flagging Rules

The two dimensions for measuring reliability considered here are

- variance, or RSE, and
- sample size.

The NCVS has historically flagged estimates of all types (rates, totals, and percentages) as unreliable when the numerator sample size is less than or equal to 10 or the percent RSE is greater than 50%. These flagging criteria can be compared with the review conducted by Klein, Proctor, Boudreault, and Turczyn (2002) of the rules used by various national surveys to flag, or suppress, unreliable estimates. A summary of their findings is presented in ***Exhibit 3A***.

Exhibit 3A. Summary of Criteria for Flagging Unreliable Estimates Used by Various National Surveys

Survey Title	Criteria for Flagging Unreliable Estimates
Behavioral Risk Factor Surveillance Survey (BRFSS)	Denominator < 50
Medical Expenditure Survey (MEPS)	Denominator < 70 or RSE > 30%
National Ambulatory Medical Care Survey (NAMCS)	Numerator < 30 or RSE > 30%
National Health Interview Survey (NHIS)	Denominator < 50 or RSE > 30%
National Health and Nutrition Examination Survey (NHANES)	Denominator < 30 or RSE > 30%
National Hospital Discharge Survey (NHDS)	Numerator < 30 or RSE > 30%
National Survey of Family Growth (NSFG)	Denominator < 50 or RSE > 30%
Youth Risk Behavior Surveillance Survey (YRBSS)	Denominator < 100 events

Note: Numerator and denominator are sample sizes. RSE, relative standard error.

Source: Klein, R. J., Proctor, S. E., Boudreault, M. A., & Turczyn, K. M. (2002). *Healthy People 2010 criteria for data suppression* (Healthy People 2010 Statistical Notes No. 24). Atlanta, GA: Centers for Disease Control and Prevention. Retrieved from http://www.cdc.gov/nchs/data/statnt/statnt24.pdf.

On the basis of the previous NCVS experience and the rules summarized in ***Exhibit 3A***, the flagging rules presented in ***Exhibit 3B*** were considered as alternatives for use with the NCVS. For each estimate type, all combinations of sample size and percent RSE values from ***Exhibit 3B*** were considered and applied to a selected set of estimates—for example, for rates, one such set of flagging criteria was numerator ≤ 30 or RSE > 30%. The number and percentage of estimates that would be flagged for each combination of criteria were tabulated and are discussed below. All RSEs were computed using the TSL variance estimation method.

Exhibit 3B. Unreliable Estimate Flagging Rules Considered

Estimate Type and Rule Set	Event Sample Size	Percent RSE
Rate (per 1,000 persons)	a. Numerator ≤ 10; b. Numerator ≤ 20; or c. Numerator ≤ 30	a. RSE > 30%; or b. RSE > 50%
Total	a. Count ≤ 10; b. Count ≤ 20; or c. Count ≤ 30	a. RSE > 30%; or b. RSE > 50%
Percentage-1	a. Denominator ≤ 10; b. Denominator ≤ 20; or c. Denominator ≤ 30	a. RSE > 30%; or b. RSE > 50%
Percentage-2	a. Numerator ≤ 10; b. Numerator ≤ 20; or c. Numerator ≤ 30	a. RSE > 30%; or b. RSE > 50%
Percentage-3	a. Denominator ≤ 10; b. Denominator ≤ 20; or c. Denominator ≤ 30	a. RSE log(p or 100−p) > 30%; or b. RSE log(p or 100−p) > 50%
Percentage-4	a. Numerator ≤ 10; b. Numerator ≤ 20; or c. Numerator ≤ 30	a. RSE log(p or 100−p) > 30%; or b. RSE log(p or 100−p) > 50%

3.3 Reliability Flagging Rules for Victimization Rates and Totals

The reliability flagging rules for victimization rates and totals are related because a total estimate is the numerator for the corresponding rate estimate. Consequently, rates and totals will be considered jointly in this section. In addition, as has been done in previous sections of this report, single-year and pooled-year estimates will be considered. Estimates were created for combinations of the victimizations types and subpopulations listed in ***Section 2.3***. Single-year estimates are for calendar years 2008–2011, whereas pooled-year estimates are for 2006–2008 and 2009–2011.

The combinations of possible rules in ***Exhibit 3B*** generate a very large number of possibilities, each of which was reviewed but is not presented here. From this review, recommended rules for flagging unreliable estimates were determined. These are presented below, followed by a summary of the characteristics of the rules.

For victimization rates and totals, the following rules are recommended.

Victimization Rates

Flag an estimate as unreliable if

RSE > 30% or

numerator sample size ≤ 10.

Victimization Totals

Flag an estimate as unreliable if

RSE > 30% or

count sample size ≤ 10.

These rules for flagging unreliable estimates are recommended because they continue several features that have been used by the NCVS for many years while tightening the RSE criteria to be consistent with those of many other major national surveys.

The percentage of estimates recommended to be flagged as unreliable is summarized in ***Exhibits 3C***, ***3D***, ***3E,*** and ***3F*** for single-year rates, pooled-year rates, single-year totals, and pooled-year totals, respectively. The percentage of estimates recommended to be flagged across domains is similar, but not identical, for rates and totals. However, the overall percentages of estimates recommended to be flagged are the same for rates and totals. Overall, 27.2% of single-year rates and totals would be flagged (***Exhibits 3C*** and ***3E***), which drops to 6.7% (***Exhibits 3D*** and ***3F***) for pooled-year rates and totals. For combinations of other criteria, the percentage of estimates flagged would be between 17.2% and 35.2% for single-year rates and totals and 1.3% and 15.0% for pooled-year rates and totals (results not shown).

3.4 Reliability Flagging Rules for Percentages of Victimizations

Percentages of victimizations are another type of estimate often created with NCVS data. Examples include the percentages of robberies committed against women or the percentage of household burglaries committed during daylight hours. A special consideration is that the RSE can become inflated for small percentages. The percent RSE for a percentage is $100 \times \sqrt{Var(P)}/P$, where P is the percentage of victimizations under study. When P is near 0%, the RSE will become large and can understate the precision of the estimated percentage. In addition, it is desirable that a reliability criterion for a percentage treat similarly the situations where P

approaches either 0% or 100% because the variance of P and $100-P$ are the same; however, the RSE for P and $100-P$ are not the same. One option is to apply the reliability criterion to either the RSE of the log(P) or log($100-P$), as is done in the National Survey on Drug Use and Health (Substance Abuse and Mental Health Services Administration, 2011). When the percentage is less than or equal to 50%, then the RSE of log(P) is considered, whereas the RSE of log($100-P$) is considered when the percentage is greater than 50%. The log transformation lessens the impact of P being near 0%, whereas the switch between P and $100-P$ makes the rule symmetric. This is the criterion included in the rows labeled Percentage-3 and Percentage-4 in ***Exhibit 3B***. The percent RSE for the log(P) is $100 \times \sqrt{Var(P)}/[P\text{abs}(\log(P/100))]$ and, for the log($100-P$), the percent RSE is $100 \times \sqrt{Var(P)}/[(100 - P)\text{abs}(\log(1 - P/100))]$.

Exhibit 3C. Number and Percentage of Single-Year Victimization Rates Flagged

	Total No. of Estimates	Percent RSE > 30%		Victimization Count ≤ 10		Percent RSE > 30% Victimization Count ≤ 10	
		Number Flagged	Percent Flagged	Number Flagged	Percent Flagged	Number Flagged	Percent Flagged
All Crime Types and Subgroups	600	157	26.17	85	14.17	163	27.17
Personal Crimes	420	155	36.91	85	20.24	161	38.33
Rape/sexual assault	84	63	75.00	25	29.76	66	78.57
Robbery	84	24	28.57	7	8.33	24	28.57
Aggravated assault	84	9	10.71	4	4.76	9	10.71
Simple assault	84	4	4.76	0	0.00	4	4.76
Personal theft	84	55	65.48	49	58.33	58	69.05
Property Crimes	180	2	1.11	0	0.00	2	1.11
Household burglary	60	0	0.00	0	0.00	0	0.00
Motor vehicle theft	60	2	3.33	0	0.00	2	3.33
Theft	60	0	0.00	0	0.00	0	0.00
Estimate Range							
0.00–0.25	18	16	88.89	18	100.00	18	100.00
0.25–0.50	34	28	82.35	28	82.35	29	85.29
0.5–1.0	70	40	57.14	28	40.00	43	61.43
1.0–5.0	217	69	31.80	11	5.07	69	31.80
5.0–75.0	207	4	1.93	0	0.00	4	1.93
75.0+	54	0	0.00	0	0.00	0	0.00

(continued)

Exhibit 3C. Number and Percentage of Single-Year Victimization Rates Flagged (continued)

	Total No. of Estimates	Percent RSE > 30%		Victimization Count ≤ 10		Percent RSE > 30% Victimization Count ≤ 10	
		Number Flagged	Percent Flagged	Number Flagged	Percent Flagged	Number Flagged	Percent Flagged
Personal Crimes by Subgroups							
Sex							
Male	20	6	30.00	4	20.00	6	30.00
Female	20	1	5.00	0	0.00	1	5.00
Race/Hispanic origin							
White	20	2	10.00	0	0.00	2	10.00
Black	20	9	45.00	7	35.00	9	45.00
Hispanic	20	10	50.00	6	30.00	10	50.00
Other	20	13	65.00	9	45.00	15	75.00
Age							
12–17	20	10	50.00	5	25.00	10	50.00
18–24	20	7	35.00	3	15.00	7	35.00
25–34	20	8	40.00	5	25.00	8	40.00
35–49	20	8	40.00	3	15.00	8	40.00
50–64	20	7	35.00	8	40.00	9	45.00
65 or older	20	19	95.00	15	75.00	19	95.00

(continued)

Exhibit 3C. Number and Percentage of Single-Year Victimization Rates Flagged (continued)

	Total No. of Estimates	Percent RSE > 30%		Victimization Count ≤ 10		Percent RSE > 30% Victimization Count ≤ 10	
		Number Flagged	Percent Flagged	Number Flagged	Percent Flagged	Number Flagged	Percent Flagged
Region							
Northeast	20	9	45.00	2	10.00	9	45.00
Midwest	20	8	40.00	2	10.00	9	45.00
South	20	4	20.00	2	10.00	4	20.00
West	20	7	35.00	1	5.00	8	40.00
Rural/urban							
Urban	20	1	5.00	0	0.00	1	5.00
Rural	20	12	60.00	6	30.00	12	60.00
MSA status							
Yes	20	1	5.00	0	0.00	1	5.00
No	20	12	60.00	7	35.00	12	60.00
Property Crimes by Subgroups							
Household income							
Less than $15,000	12	0	0.00	0	0.00	0	0.00
$15,000–$24,999	12	1	8.33	0	0.00	1	8.33
$25,000–$49,999	12	0	0.00	0	0.00	0	0.00
$50,000–$74,999	12	0	0.00	0	0.00	0	0.00
$75,000 or more	12	0	0.00	0	0.00	0	0.00
Unknown	12	0	0.00	0	0.00	0	0.00

(continued)

Exhibit 3C. Number and Percentage of Single-Year Victimization Rates Flagged (continued)

	Total No. of Estimates	Percent RSE > 30%		Victimization Count ≤ 10		Percent RSE > 30% Victimization Count ≤ 10	
		Number Flagged	Percent Flagged	Number Flagged	Percent Flagged	Number Flagged	Percent Flagged
Region							
Northeast	12	0	0.00	0	0.00	0	0.00
Midwest	12	0	0.00	0	0.00	0	0.00
South	12	0	0.00	0	0.00	0	0.00
West	12	0	0.00	0	0.00	0	0.00
Rural/urban							
Urban	12	0	0.00	0	0.00	0	0.00
Rural	12	0	0.00	0	0.00	0	0.00
MSA status							
Yes	12	0	0.00	0	0.00	0	0.00
No	12	1	8.33	0	0.00	1	8.33

Note. MSA, Metropolitan Statistical Area; RSE, relative standard error.

Exhibit 3D. Number and Percentage of Pooled-Year Victimization Rates Flagged

		Percent RSE > 30%		Victimization Count ≤ 10		Percent RSE > 30% Victimization Count ≤ 10	
	Total No. of Estimates	**Number Flagged**	**Percent Flagged**	**Number Flagged**	**Percent Flagged**	**Number Flagged**	**Percent Flagged**
All Crime Types and Subgroups	300	20	6.67	3	1.00	20	6.67
Personal Crimes	210	20	9.52	3	1.43	20	9.52
Rape/sexual assault	42	14	33.33	2	4.76	14	33.33
Robbery	42	1	2.38	0	0.00	1	2.38
Aggravated assault	42	0	0.00	0	0.00	0	0.00
Simple assault	42	0	0.00	0	0.00	0	0.00
Personal theft	42	5	11.91	1	2.38	5	11.91
Property Crimes	90	0	0.00	0	0.00	0	0.00
Household burglary	30	0	0.00	0	0.00	0	0.00
Motor vehicle theft	30	0	0.00	0	0.00	0	0.00
Theft	30	0	0.00	0	0.00	0	0.00
Estimate Range							
0.00–0.25	5	4	80.00	3	60.00	4	80.00
0.25–0.50	12	3	25.00	0	0.00	3	25.00
0.5–1.0	40	6	15.00	0	0.00	6	15.00
1.0–5.0	103	7	6.80	0	0.00	7	6.80
5.0–75.0	111	0	0.00	0	0.00	0	0.00
75.0+	29	0	0.00	0	0.00	0	0.00

(continued)

Exhibit 3D. Number and Percentage of Pooled-Year Victimization Rates Flagged (continued)

		Percent RSE > 30%		Victimization Count ≤ 10		Percent RSE > 30% Victimization Count ≤ 10	
	Total No. of Estimates	Number Flagged	Percent Flagged	Number Flagged	Percent Flagged	Number Flagged	Percent Flagged
Personal Crimes by Subgroups							
Sex							
Male	10	1	10.00	0	0.00	1	10.00
Female	10	0	0.00	0	0.00	0	0.00
Race/Hispanic origin							
White	10	0	0.00	0	0.00	0	0.00
Black	10	1	10.00	0	0.00	1	10.00
Hispanic	10	1	10.00	0	0.00	1	10.00
Other	10	3	30.00	1	10.00	3	30.00
Age							
12–17	10	1	10.00	0	0.00	1	10.00
18–24	10	1	10.00	0	0.00	1	10.00
25–34	10	0	0.00	0	0.00	0	0.00
35–49	10	1	10.00	0	0.00	1	10.00
50–64	10	4	40.00	0	0.00	4	40.00
65 or older	10	2	20.00	1	10.00	2	20.00

(continued)

Exhibit 3D. Number and Percentage of Pooled-Year Victimization Rates Flagged (continued)

	Total No. of Estimates	Percent RSE > 30%		Victimization Count ≤ 10		Percent RSE > 30% Victimization Count ≤ 10	
		Number Flagged	Percent Flagged	Number Flagged	Percent Flagged	Number Flagged	Percent Flagged
Region							
Northeast	10	0	0.00	0	0.00	0	0.00
Midwest	10	1	10.00	0	0.00	1	10.00
South	10	0	0.00	0	0.00	0	0.00
West	10	0	0.00	0	0.00	0	0.00
Rural/urban							
Urban	10	0	0.00	0	0.00	0	0.00
Rural	10	2	20.00	1	10.00	2	20.00
MSA status							
Yes	10	0	0.00	0	0.00	0	0.00
No	10	2	20.00	0	0.00	2	20.00
Property Crimes by Subgroups							
Household income							
Less than $15,000	6	0	0.00	0	0.00	0	0.00
$15,000–$24,999	6	0	0.00	0	0.00	0	0.00
$25,000–$49,999	6	0	0.00	0	0.00	0	0.00
$50,000–$74,999	6	0	0.00	0	0.00	0	0.00
$75,000 or more	6	0	0.00	0	0.00	0	0.00
Unknown	6	0	0.00	0	0.00	0	0.00

(continued)

Exhibit 3D. Number and Percentage of Pooled-Year Victimization Rates Flagged (continued)

		Percent RSE > 30%		Victimization Count ≤ 10		Percent RSE > 30% Victimization Count ≤ 10	
	Total No. of Estimates	**Number Flagged**	**Percent Flagged**	**Number Flagged**	**Percent Flagged**	**Number Flagged**	**Percent Flagged**
Region							
Northeast	6	0	0.00	0	0.00	0	0.00
Midwest	6	0	0.00	0	0.00	0	0.00
South	6	0	0.00	0	0.00	0	0.00
West	6	0	0.00	0	0.00	0	0.00
Rural/urban							
Urban	6	0	0.00	0	0.00	0	0.00
Rural	6	0	0.00	0	0.00	0	0.00
MSA status							
Yes	6	0	0.00	0	0.00	0	0.00
No	6	0	0.00	0	0.00	0	0.00

Note. MSA, Metropolitan Statistical Area; RSE, relative standard error.

Exhibit 3E. Number and Percentage of Single-Year Victimization Totals Flagged

	Total No. of Estimates	Percent RSE > 30%		Victimization Count ≤ 10		Percent RSE > 30% Victimization Count ≤ 10	
		Number Flagged	Percent Flagged	Number Flagged	Percent Flagged	Number Flagged	Percent Flagged
All Crime Types and Subgroups	600	157	26.17	85	14.17	163	27.17
Personal Crimes	420	154	36.67	85	20.24	160	38.10
Rape/sexual assault	84	64	76.19	25	29.76	67	79.76
Robbery	84	23	27.38	7	8.33	23	27.38
Aggravated assault	84	9	10.71	4	4.76	9	10.71
Simple assault	84	4	4.76	0	0.00	4	4.76
Personal theft	84	54	64.29	49	58.33	57	67.86
Property Crimes	180	3	1.67	0	0.00	3	1.67
Household burglary	60	0	0.00	0	0.00	0	0.00
Motor vehicle theft	60	3	5.00	0	0.00	3	5.00
Theft	60	0	0.00	0	0.00	0	0.00
Personal Crimes by Subgroups							
Sex							
Male	20	6	30.00	4	20.00	6	30.00
Female	20	1	5.00	0	0.00	1	5.00
Race/Hispanic origin							
White	20	2	10.00	0	0.00	2	10.00
Black	20	9	45.00	7	35.00	9	45.00
Hispanic	20	10	50.00	6	30.00	10	50.00
Other	20	12	60.00	9	45.00	14	70.00

(continued)

Exhibit 3E. Number and Percentage of Single-Year Victimization Totals Flagged (continued)

	Total No. of Estimates	Percent RSE > 30%		Victimization Count ≤ 10		Percent RSE > 30% Victimization Count ≤ 10	
		Number Flagged	Percent Flagged	Number Flagged	Percent Flagged	Number Flagged	Percent Flagged
Age							
12–17	20	10	50.00	5	25.00	10	50.00
18–24	20	7	35.00	3	15.00	7	35.00
25–34	20	8	40.00	5	25.00	8	40.00
35–49	20	8	40.00	3	15.00	8	40.00
50–64	20	7	35.00	8	40.00	9	45.00
65 or older	20	19	95.00	15	75.00	19	95.00
Region							
Northeast	20	9	45.00	2	10.00	9	45.00
Midwest	20	8	40.00	2	10.00	9	45.00
South	20	5	25.00	2	10.00	5	25.00
West	20	6	30.00	1	5.00	7	35.00
Rural/urban							
Urban	20	1	5.00	0	0.00	1	5.00
Rural	20	12	60.00	6	30.00	12	60.00
MSA status							
Yes	20	1	5.00	0	0.00	1	5.00
No	20	12	60.00	7	35.00	12	60.00

(continued)

Exhibit 3E. Number and Percentage of Single-Year Victimization Totals Flagged (continued)

		Percent RSE > 30%		Victimization Count ≤ 10		Percent RSE > 30% Victimization Count ≤ 10	
	Total No. of Estimates	Number Flagged	Percent Flagged	Number Flagged	Percent Flagged	Number Flagged	Percent Flagged
Property Crimes by Subgroups							
Household income							
Less than $15,000	12	0	0.00	0	0.00	0	0.00
$15,000–$24,999	12	1	8.33	0	0.00	1	8.33
$25,000–$49,999	12	0	0.00	0	0.00	0	0.00
$50,000–$74,999	12	0	0.00	0	0.00	0	0.00
$75,000 or more	12	0	0.00	0	0.00	0	0.00
Unknown	12	0	0.00	0	0.00	0	0.00
Region							
Northeast	12	0	0.00	0	0.00	0	0.00
Midwest	12	0	0.00	0	0.00	0	0.00
South	12	0	0.00	0	0.00	0	0.00
West	12	0	0.00	0	0.00	0	0.00
Rural/urban							
Urban	12	0	0.00	0	0.00	0	0.00
Rural	12	0	0.00	0	0.00	0	0.00
MSA status							
Yes	12	0	0.00	0	0.00	0	0.00
No	12	2	16.67	0	0.00	2	16.67

Note. MSA, Metropolitan Statistical Area; RSE, relative standard error.

Exhibit 3F. Number and Percentage of Pooled-Year Victimization Totals Flagged

	Total No. of Estimates	Percent RSE > 30%		Victimization Count ≤ 10		Percent RSE > 30% Victimization Count ≤ 10	
		Number Flagged	Percent Flagged	Number Flagged	Percent Flagged	Number Flagged	Percent Flagged
All Crime Types and Subgroups	300	20	6.67	3	1.00	20	6.67
Personal Crimes	210	20	9.52	3	1.43	20	9.52
Rape/sexual assault	42	14	33.33	2	4.76	14	33.33
Robbery	42	1	2.38	0	0.00	1	2.38
Aggravated assault	42	0	0.00	0	0.00	0	0.00
Simple assault	42	0	0.00	0	0.00	0	0.00
Personal theft	42	5	11.91	1	2.38	5	11.91
Property Crimes	90	0	0.00	0	0.00	0	0.00
Household burglary	30	0	0.00	0	0.00	0	0.00
Motor vehicle theft	30	0	0.00	0	0.00	0	0.00
Theft	30	0	0.00	0	0.00	0	0.00
Personal Crimes by Subgroups							
Sex							
Male	10	1	10.00	0	0.00	1	10.00
Female	10	0	0.00	0	0.00	0	0.00
Race/Hispanic origin							
White	10	0	0.00	0	0.00	0	0.00
Black	10	1	10.00	0	0.00	1	10.00
Hispanic	10	1	10.00	0	0.00	1	10.00
Other	10	3	30.00	1	10.00	3	30.00

(continued)

Exhibit 3F. Number and Percentage of Pooled-Year Victimization Totals Flagged (continued)

		Percent RSE > 30%		Victimization Count ≤ 10		Percent RSE > 30% Victimization Count ≤ 10	
	Total No. of Estimates	Number Flagged	Percent Flagged	Number Flagged	Percent Flagged	Number Flagged	Percent Flagged
Age							
12–17	10	1	10.00	0	0.00	1	10.00
18–24	10	1	10.00	0	0.00	1	10.00
25–34	10	0	0.00	0	0.00	0	0.00
35–49	10	1	10.00	0	0.00	1	10.00
50–64	10	4	40.00	0	0.00	4	40.00
65 or older	10	2	20.00	1	10.00	2	20.00
Region							
Northeast	10	0	0.00	0	0.00	0	0.00
Midwest	10	1	10.00	0	0.00	1	10.00
South	10	0	0.00	0	0.00	0	0.00
West	10	0	0.00	0	0.00	0	0.00
Rural/urban							
Urban	10	0	0.00	0	0.00	0	0.00
Rural	10	2	20.00	1	10.00	2	20.00
MSA status							
Yes	10	0	0.00	0	0.00	0	0.00
No	10	2	20.00	0	0.00	2	20.00

(continued)

Exhibit 3F. Number and Percentage of Pooled-Year Victimization Totals Flagged (continued)

		Percent RSE > 30%		Victimization Count ≤ 10		Percent RSE > 30% Victimization Count ≤ 10	
	Total No. of Estimates	**Number Flagged**	**Percent Flagged**	**Number Flagged**	**Percent Flagged**	**Number Flagged**	**Percent Flagged**
Property Crimes by Subgroups							
Household income							
Less than $15,000	6	0	0.00	0	0.00	0	0.00
$15,000–$24,999	6	0	0.00	0	0.00	0	0.00
$25,000–$49,999	6	0	0.00	0	0.00	0	0.00
$50,000–$74,999	6	0	0.00	0	0.00	0	0.00
$75,000 or more	6	0	0.00	0	0.00	0	0.00
Unknown	6	0	0.00	0	0.00	0	0.00
Region							
Northeast	6	0	0.00	0	0.00	0	0.00
Midwest	6	0	0.00	0	0.00	0	0.00
South	6	0	0.00	0	0.00	0	0.00
West	6	0	0.00	0	0.00	0	0.00
Rural/urban							
Urban	6	0	0.00	0	0.00	0	0.00
Rural	6	0	0.00	0	0.00	0	0.00
MSA status							
Yes	6	0	0.00	0	0.00	0	0.00
No	6	0	0.00	0	0.00	0	0.00

Note. MSA, Metropolitan Statistical Area; RSE, relative standard error.

The recommended rule is to flag as unreliable percentages of victimizations if

- the RSE > 30%, and
  - the percentage is ≤ 50%, then use the RSE of $\log(P)$
  - the percentage is > 50%, then use the RSE of $\log(100-P)$; or
- denominator sample size is ≤ 10.

The denominator sample size is recommended here because it corresponds to the sample size, or count, of victimizations used in calculating the percentage.

The various flagging rules for victimization percentages were applied to estimates for the following situations.

- Type of victimization among all victimizations
- Gender percentages among individual types of violent victimizations
- Racial percentages among individual types of violent victimizations
- Age category percentages among individual types of violent victimizations
- Regional percentages among individual types of violent and property victimizations
- Rural/urban percentages among individual types of violent and property victimizations
- MSA status percentages among individual types of violent and property victimizations
- Income category percentages among individual types of property victimizations
- Time of day category percentages among all types and among individual types of violent and property victimizations, by gender, race, and region
- Police notified category percentages among all types and among individual types of violent and property victimizations, by gender, race, and region
- Victim relationship category percentages among all types and among individual types of violent victimizations, by gender, race, and region
- Weapon involvement category percentages among all types and among individual types of violent victimizations, by gender, race, and region
- Time of day category percentages among individual types of property victimizations, by MSA status

- Police notified category percentages among individual types of property victimizations, by MSA status

Exhibit 3G presents the number and percentage of estimates recommended to be flagged as unreliable. For single-year victimization percentages, 20.5% of estimates are recommended for flagging, with most of these resulting from the RSE criterion. The increased sample sizes associated with pooling years of data reduce the estimates recommended for flagging to 7.3%, with all of these resulting from the RSE criterion. Flagging criteria based upon the RSE of P, rather than the RSE of the log of P or $100-P$, would have flagged many more estimates—over 40.1% and 25.7% for single-year and pooled-years estimates, respectively, for a percent RSE > 30%.

Exhibit 3G. Number and Percentage of Victimization Percentages Flagged

	Total No. of Estimates	RSE of the Log > 30%		Denominator Count ≤ 10		RSE of the Log > 30% Denominator Count ≤ 10	
		Number Flagged	Percent Flagged	Number Flagged	Percent Flagged	Number Flagged	Percent Flagged
Single-Year Percentages							
All Crime Types and Subgroups	4,329	877	20.26	307	7.09	887	20.49
Percentage Range							
0.00–0.25	6	0	0.00	0	0.00	0	0.00
0.25–0.50	16	0	0.00	0	0.00	0	0.00
0.50–1.00	96	0	0.00	0	0.00	0	0.00
1.00–5.00	459	38	8.28	1	0.22	38	8.28
5.00–75.00	3,452	759	21.99	255	7.39	764	22.13
75.00+	300	80	26.67	51	17.00	85	28.33
Pooled-Year Percentages							
All Crime Types and Subgroups	2,336	171	7.32	18	0.77	171	7.32
Percentage Range							
0.00–0.25	3	0	0	0	0.00	0	0.00
0.25–0.50	25	0	0.00	0	0.00	0	0.00
0.50–1.00	48	0	0.00	0	0.00	0	0.00
1.00–5.00	326	13	3.99	0	0.00	13	3.99
5.00–75.00	1,807	150	8.30	16	0.89	150	8.30
75.00+	127	8	6.30	2	1.57	8	6.30

Note. RSE, relative standard error.

SECTION 4. CONFIDENCE INTERVALS

4.1 Introduction

A CI is used to convey the precision with which a value has been estimated, along with the associated level of confidence, expressed as a percentage. For example, a 95% CI is said to have a 95% chance of including the true population value under study. A 95% standard normal CI for an estimate Y is constructed as $Y \pm 1.96 \times SE(Y)$, where $SE(Y)$ is the standard error of Y given by $SE(Y) = \sqrt{Var(Y)}$. A complication for victimization rates and totals is that the lower end point of the CI might be negative, or fall below zero, whereas a rate or total cannot be negative. Likewise, a victimization percentage is constrained to be between 0% and 100%, whereas its standard normal CI could include values outside of this range. To avoid such situations, range-preserving transformations are used to first transform an estimate to a different scale. A CI is then calculated on the new scale and then transformed back to the original scale of the estimate. For victimization rates and totals, a natural logarithm, or log, transformation will be considered, and a logit transformation will be considered for percentages.

A log-transform CI for either a rate or total starts by transforming the original value Y to $Z = \log(Y)$ and its standard error to $SE(Z) = SE(Y)/Y$. Then, the lower and upper end points of the 95% CI for Z are $Z_l = Z - 1.96 \times SE(Z)$ and $Z_u = Z + 1.96 \times SE(Z)$, respectively. Transforming back to the scale of either the rate or total, the lower and upper end points of the 95% CI for Y are $Y_l = \exp(Z_l)$ and $Y_u = \exp(Z_u)$, respectively. The resulting CI for a rate or total will not include any negative values.

The similar process for a victimization percentage is slightly more complicated because it must be bounded to be between 0% and 100%. The logit transformation for a proportion will be used to achieve this property for the CI of a percentage. First, the percentage, P, is changed to its corresponding proportion as $p = P/100$ along with $SE(p) = SE(P)/100$. The logit transformation of p is $z = \log[p/(1-p)]$ and its standard error is $SE(z) = SE(p)/[p(1-p)]$. The lower and upper end points of the 95% CI for z are $z_l = z - 1.96 \times SE(z)$ and $z_u = z + 1.96 \times SE(z)$, respectively. Then, the lower and upper end points of the 95% CI for P are $P_l = 100 \times e^{z_l}/(1 + e^{z_l})$ and $P_u = 100 \times e^{z_u}/(1 + e^{z_u})$.

For the same set of estimates used in ***Section 3*** to study estimate reliability, 95% CIs were created using both standard normal and transformed CIs based on the TSL variance estimation approach. These are discussed in the following sections.

4.2 Confidence Intervals for Victimization Rates

Exhibit 4A displays a summary of the CIs for single-year and pooled-year victimization rates. For single-year rates, the upper portion of ***Exhibit 4A***, 40 out of 630 of the standard normal 95% CIs include lower end points that were negative, whereas, by design, none of the log-transform CIs include a negative lower end point. In addition, the median lengths of the standard normal and the log-transform CIs are very similar. The median percentage of the length of the CI to the left of the estimate is presented as a measure of asymmetry of the log-transform CIs. A symmetrical CI would have 50% of its length to the left of the estimate. As expected, the smaller rates are more asymmetric with a lower percentage to the left of the estimate, but the percentage steadily increases toward 50% as the rate increases. The pooled-year rates, the lower portion of ***Exhibit 4A***, display a very similar pattern but with far fewer negative lower end points and shorter CI lengths because of the increased sample size and precisions associated with pooling data across years.

4.3 Confidence Intervals for Victimization Totals

A summary of CIs for single-year and pooled-year victimization totals is given in ***Exhibit 4B***. Forty-two out of 630 of the standard normal CIs include a negative lower end point for single-year totals, whereas two lower end points are negative for pooled-year totals. As before, the log-transform CIs are all positive and are largely symmetrical, with the median percentages to the left of the estimate being over 40% for both single-year and pooled-year totals. Finally, the median lengths of the standard normal and the log-transform CIs are close, with the log-transform CIs being slightly larger.

Exhibit 4A. Confidence Interval Summary for Single-Year and Pooled-Year Victimization Rates

	All Rates	Rates 0.00–0.25	Rates 0.25–0.50	Rates 0.50–1.00	Rates 1.00–5.00	Rates 5.00–75.00	Rates 75.0+
Single-Year Rates							
Number of Confidence Intervals (CIs)	630	16	34	75	229	218	58
Standard Normal Method							
Number of negative lower end points	40	3	5	6	16	0	0
Median length of the CI	2.8	0.4	0.6	0.8	2.1	6.5	20.4
Log Transform Method							
Number of negative lower end points	0	0	0	0	0	0	0
Median length of the CI	3.1	0.5	0.7	0.9	2.2	6.6	20.5
Median % left of estimate	41.3	23.7	29.3	35.0	39.2	44.0	47.5
Pooled-Year Rates							
Number of CIs	316	5	12	42	108	118	31
Standard Normal Method							
Number of negative lower end points	2	1	1	0	0	0	0
Median length of the CI	2.0	0.3	0.3	0.6	1.4	3.7	14.3
Log Transform Method							
Number of negative lower end points	0	0	0	0	0	0	0
Median length of the CI	2.0	0.4	0.3	0.6	1.4	3.7	14.3
Median % left of estimate	44.7	33.1	37.8	39.8	43.3	46.3	48.4

Exhibit 4B. Confidence Interval Summary for Single-Year and Pooled-Year Victimization Totals

	Single-Year Totals	Pooled-Year Totals
Number of Confidence Intervals (CIs)	630	316
Standard Normal Method		
Number of negative lower end points	42	2
Median length of the CI	175,302	347,344
Log Transform Method		
Number of negative lower end points	0	0
Median length of the CI	187,279	353,294
Median % left of estimate	41.4	44.6

4.4 Confidence Intervals for Percentages of Victimizations

Exhibit 4C presents a summary of the CIs for single-year and pooled-year percentages of victimizations. The end points of standard normal CIs can be less than 0% or exceed 100% for percentages. For single-year percentages, this occurred over 1,000 times for the data considered here, with smaller percentages making up the majority of the cases. The logit-transform CIs remove this problem while making the median CI lengths very slightly longer than those for the standard normal CIs. Considering the median percentage of the length of the CI to the left of the estimate, the CIs for percentages with values around 50% are approximately symmetrical, with approximately the same amount of the CI to the left of the percentage (49%) as to the right (51% = 100%–49%). The CIs become more asymmetrical as the value of the percentages moves toward 0% or 100%. This is expected as the logit-transformation keeps the CIs bounded between 0% and 100%. For percentages of victimizations from pooled years, the results are very similar; however, both the numbers of CIs extending outside of 0% to 100% and the median lengths of the CIs are reduced, which results from the increase in precision when pooling years to increase the sample size.

Exhibit 4C. Confidence Interval Summary for Single-Year and Pooled-Year Percentages of Victimizations

	All Percentages	Percentages 0–5	Percentages 5–10	Percentages 10–25	Percentages 25–75	Percentages 75–90	Percentages 90–95	Percentages 95–100
Single-Year Percentages								
Number of Confidence Intervals (CIs)	4,329	577	542	1,022	1,888	206	78	16
Standard Normal Method								
Number of end points outside of 0% to 100%	1,002	355	214	196	137	60	31	9
Median length of the CI	17	5	12	17	27	24	12	8
Logit Transform Method								
Number of end points outside of 0% to 100%	0	0	0	0	0	0	0	0
Median length of the CI	18	7	13	18	27	24	14	9
Median % left of estimate	44.9	23.5	32.3	40.5	49.0	64.2	68.4	76.5
Pooled-Year Percentages								
Number of Confidence Intervals	2,336	402	283	500	1,024	80	43	4
Standard Normal Method								
Number of end points outside of 0% to 100%	326	198	56	43	13	10	4	2
Median length of the CI	10	4	7	10	18	13	7	5
Logit Transform Method								
Number of end points outside of 0% to 100%	0	0	0	0	0	0	0	0
Median length of the CI	10	5	7	10	18	13	8	6
Median % left of estimate	46.3	27.9	39.0	43.9	49.3	58.5	60.9	70.5

SECTION 5. FINDINGS AND RECOMMENDATIONS

The findings and recommendations of this report are presented in ***Exhibit 5***.

Exhibit 5. Findings and Recommendations for Variance Estimation, Estimate Reliability, and Confidence Intervals for the National Crime Victimization Survey

Findings	Recommendations
Variance Estimation: Generalized Variance Function (GVF) Method	
• GVF method works well for situations for which is was developed. Evaluated method with rates and totals for – estimates from single years and pooled years; and – tests of difference between single years and pooled years. • GVF method consistent with Taylor series linearization (TSL) method for the situation evaluated. • Method not appropriate for situations not considered when creating the GVFs. • Care must be taken when determining which version of the GVFs to use (e.g., based on estimate type, inclusion/exclusion of series victimizations). • Simple to use when a small number of estimates are to be processed. Cumbersome when a large number of estimates are involved.	• GVF method can be used with victimization rates and totals in the following situations: – for estimates from single years and pooled years; and – for tests of difference between single years and pooled years. • Carefully select the correct GVF version corresponding to the application under consideration.
Variance Estimation: Taylor Series Linearization (TSL) Method	
• Adequate information and variables are available on the National Crime Victimization Survey (NCVS) public use files to support TSL direct variance estimation. Evaluated method with rates, totals, and percentages for – estimates from single years and pooled years; and – tests of differences between single years and pooled years (rates and totals only). • TSL method able to capture complex design features, including primary sampling unit (PSU) sampling once every 10 years. • Statistical theory supports use of TSL method for a wide set of analysis methods beyond rates, totals, and percentages. • TSL method requires merging of person and household data files with victimization data files. Special merging procedures required.	• TSL method recommended for direct variance estimation with NCVS public use data. • Follow instructions given in Users Guide (Shook-Sa, Couzens, & Berzofsky, 2014) to implement TSL method due to special procedures required when merging person and household data files with victimization data files to construct analysis files.

• TSL method supported by statistical analysis packages including SPSS, SUDAAN, SAS, and STATA (complex samples package).	

(continued)

Exhibit 5. Findings and Recommendations for Variance Estimation, Estimate Reliability, and Confidence Intervals for the National Crime Victimization Survey (continued)

Findings	Recommendations
Variance Estimation: Balanced Repeated Replication (BRR) Method	
• Adequate information and variables are available on the NCVS public use files to support BRR direct variance estimation for single-year estimates. Evaluated method for rates and totals from single years. • For single-year estimates, BRR method produced variance estimates nearly identical to those of the TSL method. • BRR method requires a very complex data configuration to capture changes in PSU sampling every 10 years, especially for pooled-year estimates and across-year comparisons. • BRR replicate weights had to be created from pseudo-stratum and half-sample variables (recently, BRR replicate weights have been made available for some years). • BRR method requires merging of person and household data files with victimization data files. Special merging procedures required. • BRR method supported by statistical analysis packages including SUDAAN, SAS, and STATA. BRR not supported by SPSS.	• BRR method not recommended as primary direct variance estimation method with NCVS public use data. • BRR method is suited for single-year estimates.
Flagging and Suppression of Unreliable Estimates	
• Criteria from other major national surveys included – most flagged or suppressed if percent relative standard error (RSE) > 30%; and – most had additional criteria involving minimum numerator or denominator sample sizes. • Evaluated many rules combining criteria across – maximum allowable RSE and – minimum sample sizes. • Percentages of victimizations required special treatment using the RSE of the natural logarithm of the percentages.	• Rules for victimization rates: flag as unreliable if o RSE > 30% or o numerator sample size ≤ 10. • Rules for victimization totals: flag as unreliable if o RSE > 30% or o count sample size ≤ 10. • Rules for percentages of victimizations: flag as unreliable if o RSE of log(P) > 30% when P ≤ 50%; o RSE of log(100−P) > 30% when P > 50%; or o denominator sample size ≤ 10.

(continued)

Exhibit 5. Findings and Recommendations for Variance Estimation, Estimate Reliability, and Confidence Intervals for the National Crime Victimization Survey (continued)

<table>
<tr><th>Findings</th><th>Recommendations</th></tr>
<tr><th colspan="2">Confidence Intervals (CIs)</th></tr>
<tr><td>• CIs for victimization rates and totals:
– standard normal CIs yield negative lower end points for some rates and totals;
– log-transform CIs range solely over positive values; and
– median lengths of standard normal and log-transform CIs are similar, with the log-transform CIs being slightly longer.
• CIs for percentages of victimizations:
– standard normal CIs yield end points outside the range of 0% to 100%;
– logit-transform CIs bounded between 0% and 100%; and
– median lengths of standard normal and logit-transform CIs are similar, with the logit-transform CIs being slightly longer.</td><td>• Log-transform CIs recommended for victimization rates and totals.
• Logit-transform CIs recommended for percentages of victimizations.</td></tr>
</table>

SECTION 6. REFERENCES

Ash, S. (2010). Using successive difference replication for estimating variances. In *Proceedings of the Survey Research Methods Section, American Statistical Association* (pp. 3534–3548). Alexandria, VA: American Statistical Association. Retrieved from http://www.amstat.org/sections/srms/proceedings/y2011/Files/302108_67867.pdf

Bureau of Justice Statistics (BJS), Office of Justice Programs, U.S. Department of Justice. (2010). *National Crime Victimization Survey codebook, 2010* (ICPSR31202-v2). Ann Arbor, MI: Inter-university Consortium for Political and Social Research [distributor], 2012-06-22. Available at http://doi.org/10.3886/ICPSR31202.v2

Cochran, W. G. (1977). *Sampling techniques*. New York, NY: Wiley.

Fay, R. E., & Train, G. F. (1995). Aspects of survey and model-based postcensal estimation of income and poverty characteristics for states and counties. In *Proceedings of the Government Statistics Section, American Statistical Association* (pp. 154–159). Alexandria, VA: American Statistical Association.

Klein, R. J., Proctor, S. E., Boudreault, M. A., & Turczyn, K. M. (2002). *Healthy People 2010 criteria for data suppression* (Healthy People 2010 Statistical Notes No. 24). Atlanta, GA: Centers for Disease Control and Prevention. Retrieved from http://www.cdc.gov/nchs/data/statnt/statnt24.pdf

Lauritsen, J. L., Owens, J. G., Planty, M. R., & Truman, J. L. (2012). *Methods for counting high-frequency repeat victimizations in the National Crime Victimization Survey* (NCJ No. 237308). Washington, DC: Bureau of Justice Statistics. Retrieved from http://www.bjs.gov/content/pub/pdf/mchfrv.pdf

Lumley, T. (2008). Balanced repeated replication (BRR). In P. J. Lavrakas (Ed.), *Encyclopedia of survey research methods*. Newbury Park, CA: Sage.

Särndal, C. E., Swensson, B., & Wretman, J. (1992), *Model assisted survey sampling*. New York, NY: Springer-Verlag.

Shook-Sa, B., Couzens, G. L, & Berzofsky, M. (2014). *National Crime Victimization Survey (NCVS) direct variance user's guide*. Prepared for the Bureau of Justice Statistics, Washington, DC.

Substance Abuse and Mental Health Services Administration. (2011). *Results from the 2010 National Survey on Drug Use and Health: Summary of national findings* (NSDUH Series H-41, HHS Publication No. (SMA) 11-4658). Rockville, MD: Author.

Williams, R. L. (2000). A note on robust variance estimation for cluster-correlated data. *Biometrics, 56*, 218–219.

Williams, R. L. (2008). Taylor series linearization. In P. J. Lavrakas (Ed.), *Encyclopedia of survey research methods*. Newbury Park, CA: Sage.

Wolter, K. M. (1985). *Introduction to variance estimation*. New York, NY: Springer-Verlag.

The Bureau of Justice Statistics of the U.S. Department of Justice is the principal federal agency responsible for measuring crime, criminal victimization, criminal offenders, victims of crime, correlates of crime, and the operation of criminal and civil justice systems at the federal, state, tribal, and local levels. BJS collects, analyzes, and disseminates reliable and valid statistics on crime and justice systems in the United States, supports improvements to state and local criminal justice information systems, and participates with national and international organizations to develop and recommend national standards for justice statistics. William J. Sabol is director.

NCJ249242

Office of Justice Programs
Innovation • Partnerships • Safer Neighborhoods
www.ojp.usdoj.gov