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Current Population Survey Volunteer Supplement Data: Variance Estimates by the Replication Method

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Abstract

The article shows the value of ensuring data users are aware of intricacies with using survey data to infer the volunteerism characteristics of the U.S. population. Understanding volunteerism population trends in the United States (U.S.) is important for researchers and administrators. Although this paper uses complex statistical methods, it presents easy-to-understand information on the U.S. volunteer population. Readers are provided with the statistical program used to create detailed population estimates and their variances. Analyst used microdata files from 2011 through 2015 from the Volunteering Supplement of the Current Population Survey. Study used volunteer, race, and ethnicity information from a total of 445,148 survey respondents over the 2011-2015 period. Between-group comparisons suggest Non-Latino-Whites (NLW) had the highest rate of volunteerism of any other race-ethnic group. For the most part, results suggest volunteerism rates may not differ significantly between Non-Latino-Blacks (NLB) and Non-Latino-Others (NLO). Latinos (LAT) had the lowest rate of volunteerism than any other race-ethnic group. Temporal trends suggest volunteerism rate decreased for NLWs and NLOs and did not change for LATs and NLBs.

Key Words: variance, replicate, weights, demography, sociology, equity

Introduction

There is a detrimental gap in the volunteerism literature. No previous study has shown how replicate weights can be used to conduct between-group differences. The purpose of this paper is to show how replicate weights can be used to compare groups. Since its implementation in 2002, the Volunteering Supplement of the Current Population Survey (CPS), sponsored by the U.S. Census Bureau and United States (U.S.) Bureau of Labor Statistics (BLS), is a primary source for estimating the demographic characteristics of the population who volunteers (DSMD, 2006). Over decades, investigators have used data from the Volunteering Supplement of CPS to study:

- demographic characteristics of U.S. individuals who volunteer (Pho, 2004),
- spousal influence on volunteering (Rotolo & Wilson, 2006),
- gender segregation in volunteer work (Rotolo & Wilson, 2007),
- greater propensity of those who do volunteer work to respond to surveys (Abraham, Helms,& Presser, 2009),
- proxy responses generally underreport volunteering (Nesbit, 2010),
- disaster relief service volunteers (Rotolo & Berg, 2011),
- the relationship between military service and volunteering (Nesbit & Reingold, 2011),
- and compare it with other major volunteering studies (Nesbit, 2011),
- between-state differences in volunteerism (Rotolo & Wilson, 2012),
- Hispanic volunteering (Carreno, 2012),
- impact of policies on volunteerism (Nesbit & Brudney, 2013),
- what affects Hispanic volunteering (Wang, Yoshioka, & Ashcraft, 2013),
- volunteerism amongst Millennial generation (Ertas, 2016),

- to produce community-level volunteering measures (Neymotin, 2016),
- 2005-2015 trends in volunteer mentoring (Raposa, Dietz, & Rhodes. 2017),
- How individual's demographics draws them to different kinds of volunteer organizations (Nesbit, 2017),
- to show inflow of immigrants affects volunteering in receiving communities (Freire & Li, 2018), and
- to investigate linkages between labor market experiences and volunteer activities (Wiertz & Lim, 2019).

While the vast body of work, using data from the Volunteering Supplement of the CPS, includes the use of complex statistical methods, there is a notable gap in the literature. The use of *replicate weights* is almost non-existent in studies using data from the Volunteering Supplement of the CPS. This is a detrimental limitation because replicate weights can help researchers produce high-quality measures of variance (i.e., range of precision in estimate) for the sample-derived estimates. According to statistical theory, the Standard Error (SE) of an estimate captures how an inferred characteristic of the population varies across multiple samples. Because we cannot ever know the true SE of any estimate from the Volunteering Supplement of the CPS, we estimate sample SEs. Replicate weights allow the single Volunteering Supplement of the CPS sample to simulate multiple samples. Simulating multiple samples allows us to generate more precise SE estimates to improve the quality of confidence intervals.

Because not everyone in the population is administered a survey, statisticians produce population "estimates"—i.e., scientifically derived guesses. Quantitative researchers are aware that population estimates are accompanied by a measure of accuracy. By using a variance measure, data interpreters can then give statements such as: "there may be between 90 and 110 volunteers”. In this instance, the Lower Confidence Limit (LCL) would be 90 and the Upper Confidence Limit (UCL) would be 110. By using confidence limits, data users will be more aware of the complexities involved with inferring population characteristics from sample data. The specific aim of this analysis was to show how replicate weights can be used to produce high quality variance estimates.

The use of replicate weights to produce variance measures for sample estimates is common amongst researchers using American Community Survey (ACS) Public Use Microdata Sample (PUMS) files. For example, previous work has highlighted the value of using variance estimates to infer characteristics of the population from ACS data (Siordia & Le, 2013; Siordia 2014a; Siordia 2015a), to point out the use of proxy responses in ACS (Siordia, 2014b), and presence of response allocations in ACs (Siordia & Young, 2013; Siordia, 2015b). Similar data treatments are absent in the literature using data from the Volunteering Supplement of the CPS. This analysis shows how replicate weights can be used to produce easy-to-understand, but statistically sophisticated, estimates of the population to compare between-groups and within-groups over time.

Methods

Data

Study used Volunteer Data File and Non-Response Replicate Weight Data Files from the Volunteering Supplement of the CPS to explore between-group differences and within-group differences over time (i.e., temporal trends) between 2011 and 2015. Anyone with an internet connection can access all these public-use microdata files. The CPS is a monthly survey of approximately 60,000 occupied households (approximately 150,000 adults), from all 50 states and the District of Columbia. The CPS questionnaire is a completely computerized document that is administered by Census Bureau field representatives across the country through both personal and telephone interviews. Interviewers were provided with a two-hour home study for completing the basic CPS labor force exercises, supplement exercises, and a practice interview concerning the supplement. To be eligible to participate in the CPS, individuals must be 15 years of age or over and not in the Armed Forces. People in institutions, such as prisons, long-term care hospitals, and nursing homes are ineligible to be interviewed in the CPS. Proxy responses were allowed if attempts for a self-response were unsuccessful. The person who responds is called the *reference person* and usually owns or rents the housing unit (Kostanich & Dippo, 2002). All persons eligible for the labor force items of the basic CPS were also eligible for the volunteer supplement.

The analysis only focused on years 2011 through 2015 because the Non Response Replicate Weight Data Files are readily available for data 2011 onward, because the Volunteering Supplement of the CPS was not administered in 2016, and because it underwent substantial modifications in 2017. The analytic sample only includes individuals with useful information for one of the volunteer questions: the race, and ethnicity question. From the available 756,185 observations in the five files, 70% (530,521) were eligible to participate in the volunteering supplement. From those eligible to participate with the Volunteering Supplement of the CPS, 84% (445,148) of observations were included in the analysis. This means 16% (85,373) of individuals were excluded from analysis because they did not have a yes or no response to one of the volunteering questions.

Volunteerism Questions

Two questions were used to determine if a person was a volunteer: (1) *Since September 1st of last year, have you done any volunteer activities through or for an organization*?; and (2)

Sometimes people don't think of activities they do infrequently or activities they do for children's schools or youth orgs as volunteer activities. Since September 1st of last year, have you done any of these types of volunteer activities? If persons responded with a "yes" to either of these questions, they were coded as being a volunteer.

Variance Estimate via Replicate Weights

To determine the characteristics of a population by using a probability sample, researchers could repeatedly conduct sample selection, data collection, and estimation creation. The dispersion of the estimates from the replicated studies could then be used to measure the variance of the full sample (DSMD, 2006). Because this is not feasible, data creators " draw a set of random subsamples from the full sample surveyed each month, using the same principles of selection as those used for the full sample, and to apply the regular CPS estimation procedures to these subsamples, which are called replicates" (DSMD, 2006: Page 14-1). The theoretical basis for the successive difference method discussed by Wolter (1985) informed the successive difference replication method proposed by Fay and Train (1995).

The 160 replicate weights in the Volunteering Supplement of the CPS can be used to create the 160 replicate estimates necessary to calculate total variance. The total variance for a point estimate can be calculated by plugging the replicate weight estimates and the point estimate into the following formula:

$$Var(\hat{x}_0) = \frac{4}{160}\sum_{i=1}^{160}(\hat{x}_i - \hat{x}_0)^2$$

where $\hat{x}_0$ is the point estimate using the weight for the full sample and $\hat{x}_i$ are the 160 point estimates using replicate weights. Readers should note some researchers using the Volunteering

Supplement of the CPS use Generalized Variance Functions (GVFs) to create Margin of Error (MOE) for estimates.

Statistical Approach

The statistical program, written in Statistical Analytics Software, version 9.4 (SAS Institute, Cary, NC), is given in the Appendix. Analysis used 95% confidence intervals to determine when between-group and within-group over-time differences merit further research attention. The study does not adopt the traditional *statically significant* language that is ubiquitous in quantitative literature. There are many reasons for using the proposed approach. The American Statistical Association has argued statistical significance is *not* the only informative metric (Wasserstein & Lazar, 2016), and for decades statisticians have discussed the misuse of *P* values (Gigerenzer, 2004; Goodman, 2008; Cummings & Koepsell, 2010; Gelman & Loken, 2014; Greenland, Senn, Rothman, Carlin, Poole, Goodman, & Altman,, 2016; Chavalarias, Wallach, Li, & Ioannidis, 2016; Van Calster, Steyerberg, Collins, & Smits, 2018). As a result, the study only used confidence intervals (CIs) to ascertain the importance of between-group and within-group temporal differences. Readers should be aware that the absence of statistical significance does not unequivocally mean the association is uninformative or unimportant. The statistical program produces multiple measures of variance. The current analysis provides the following for each of the year-, volunteer status-, race-ethnicity-specific groups:

- unweighted count,
- population weighted count,
- 95% lower confidence limit,
- 95% upper confidence limit, and the

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- Coefficient of Variation (CV).

The CV is the SE of the estimate divided by the estimate expressed as percentage. Smaller CV indicate a narrower confidence limit. SE is the square root of the estimate of variance.

Results

Table 1 presents descriptive statistics stratified by year, volunteer status, race, and ethnicity. Descriptions for the acronym headings are provide below the table. From Table 1, readers will be able to contrast the number of individuals who actually participated in the survey (unweighted count) and how population-weighted estimates compare. Detailed information in Table 1 can be used in different ways. For example, by comparing unweighted and weighted numbers, readers will be able to see that on average, each LAT and NLB survey respondent represents more of their counterparts that NLWs and NLOs. More technically, LATs and NLBs on average have higher population weights than NLWs and NLOs. For example, in 2011, about 3,178 (5,297,962÷1,667) LATs were represented by one LAT who actually participated with the survey and number for NLWs is 2,371. These types of calculations will also show that information on fewer people is being used in more recent surveys to infer the characteristics of the population. That is, on average survey respondents were assigned larger population weights in 2015 that in 2011. This phenomenon may explain why most population estimates are less stable in 2015 than in 2011—i.e., Coefficient of Variation (CV) are higher in 2015 than in 2011 for five out of eight groups (V:LAT, V:NLW, V:NLO, NV:LAT, and NV:NLO). Note the table provides all the necessary information for those who decide *P* values are necessary. The p-value can be searched after computing z-score as follows:

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$$z = (Wgt_1 - Wgt_2) \div \sqrt{\left(\frac{Wgt_1 - LCL_1}{1.96}\right) - \left(\frac{Wgt_2 - LCL_2}{1.96}\right)}$$

where (Wgt - LCL) is the MOE and comparisons are being made between one estimate (Wgt_1) and another (Wgt_2).

Table 1

Detailed statistics by volunteer status, race, and ethnicity

Year	Group	Unw	Wgt	LCL	UCL	CV
2011	V: LAT	1,667	5,297,962	4,997,531	5,598,393	2.9%
2011	V: NLW	21,348	50,608,069	49,743,922	51,472,215	0.9%
2011	V: NLB	1,831	5,831,900	5,466,094	6,197,707	3.2%
2011	V: NLO	1,459	3,699,552	3,457,151	3,941,953	3.3%
2011	NV: LAT	9,000	30,091,327	29,785,539	30,397,115	0.5%
2011	NV: NLW	44,913	112,556,274	111,684,759	113,427,788	0.4%
2011	NV: NLB	6,934	22,590,204	22,199,520	22,980,888	0.9%
2011	NV: NLO	5,193	12,781,061	12,514,718	13,047,404	1.1%
	Group	**Unw**	**Wgt**	**LCL**	**UCL**	**CV**
2012	V: LAT	1,704	5,787,830	5,466,173	6,109,486	2.8%
2012	V: NLW	20,747	49,673,496	48,851,729	50,495,263	0.8%
2012	V: NLB	1,873	6,082,801	5,752,656	6,412,946	2.8%
2012	V: NLO	1,496	4,148,435	3,873,990	4,422,879	3.4%
2012	NV: LAT	9,201	31,977,932	31,651,322	32,304,541	0.5%
2012	NV: NLW	44,704	112,716,722	111,909,624	113,523,820	0.4%
2012	NV: NLB	6,724	22,525,999	22,173,176	22,878,823	0.8%
2012	NV: NLO	5,151	14,314,535	13,982,272	14,646,798	1.2%
	Group	**Unw**	**Wgt**	**LCL**	**UCL**	**CV**
2013	V: LAT	1,716	6,017,306	5,665,096	6,369,516	3.0%
2013	V: NLW	19,079	48,160,980	47,259,225	49,062,734	1.0%
2013	V: NLB	1,662	5,495,339	5,181,755	5,808,923	2.9%
2013	V: NLO	1,343	3,969,351	3,707,790	4,230,912	3.4%
2013	NV: LAT	8,876	32,534,185	32,176,079	32,892,290	0.6%
2013	NV: NLW	43,194	114,679,521	113,761,616	115,597,426	0.4%
2013	NV: NLB	6,816	23,760,356	23,383,731	24,136,981	0.8%
2013	NV: NLO	5,151	15,114,051	14,806,972	15,421,130	1.0%
	Group	**Unw**	**Wgt**	**LCL**	**UCL**	**CV**
2014	V: LAT	1,721	6,164,646	5,782,775	6,546,517	3.2%
2014	V: NLW	19,136	47,661,371	46,748,561	48,574,181	1.0%
2014	V: NLB	1,781	5,942,379	5,593,718	6,291,040	3.0%
2014	V: NLO	1,467	4,047,791	3,783,284	4,312,297	3.3%
2014	NV: LAT	8,975	33,295,472	32,907,082	33,683,863	0.6%
2014	NV: NLW	44,258	115,642,870	114,738,623	116,547,118	0.4%
2014	NV: NLB	7,088	23,779,678	23,392,166	24,167,190	0.8%
2014	NV: NLO	5,399	15,508,395	15,178,091	15,838,699	1.1%
	Group	**Unw**	**Wgt**	**LCL**	**UCL**	**CV**
2015	V: LAT	1,651	6,355,833	5,929,007	6,782,659	3.4%
2015	V: NLW	17,211	47,218,990	46,402,191	48,035,790	0.9%
2015	V: NLB	1,688	6,018,628	5,676,271	6,360,986	2.9%
2015	V: NLO	1,262	4,102,294	3,807,794	4,396,794	3.7%
2015	NV: LAT	8,499	34,347,571	33,921,677	34,773,464	0.6%
2015	NV: NLW	41,322	116,256,341	115,440,854	117,071,829	0.4%
2015	NV: NLB	6,887	24,281,746	23,912,244	24,651,249	0.8%
2015	NV: NLO	5,021	16,216,180	15,856,791	16,575,569	1.1%

V=Volunteer; NV=Non-volunteer; LAT=Hispanic; NLW=Non-Hispanic-White; NLB= Non-Hispanic-Black; NLO= Non-Hispanic-Other; Unw=Unweighted; Wgt=Weighted; LCL=Lower Confident Limit at 95%; UCL=Upper Confident Limit at 95%; CV=Coeficient of Variation

Figure 1 shows how data from Table 1 can be used to create easy-to-understand visualizations of volunteerism data. Data were extracted from Table 1 to provide one between-group comparison and two within-group over-time comparisons. The CIs for LATs and NLWs were used to visualize the potential number of volunteers per-year. In technical terms, 95% CIs can be used to safely expect ninety-five percent of population estimates to be within two SEs of the mean of all possible sample estimates. Albeit esoteric, this statement captures the idea that when we are using a sample of the population, we can only scientifically guess the “true” population characteristic. Following previous advice, if CIs overlapped at all between-groups or within-group over-time, then it was inferred that there may have been *no* difference between-groups and/or within-group over-time.

For example, doing a between-group comparison, we see NLWs had higher rates of volunteerism that LATs. That is, NLWs’ CIs were higher than LATs’ and their CIs did not intersect at any point. Because the CIs did not intercept at any point, the between-group difference may signal the difference in volunteerism rate between NLWs and LATs merits further research attention. Doing a within-group and over-time comparison, we see that for LATs, all their CIs intersected at around 15% across all the five years under observation. We could interpret this to mean that the volunteerism rate for LATs from 2011 to 2015 may *not* have changed. That is, the true population characteristics may not have varied over five year period. In stark contrast, we see that temporal trend for NLWs did decrease (e.g., CIs in 2011 and 2015 do *not* intercept).

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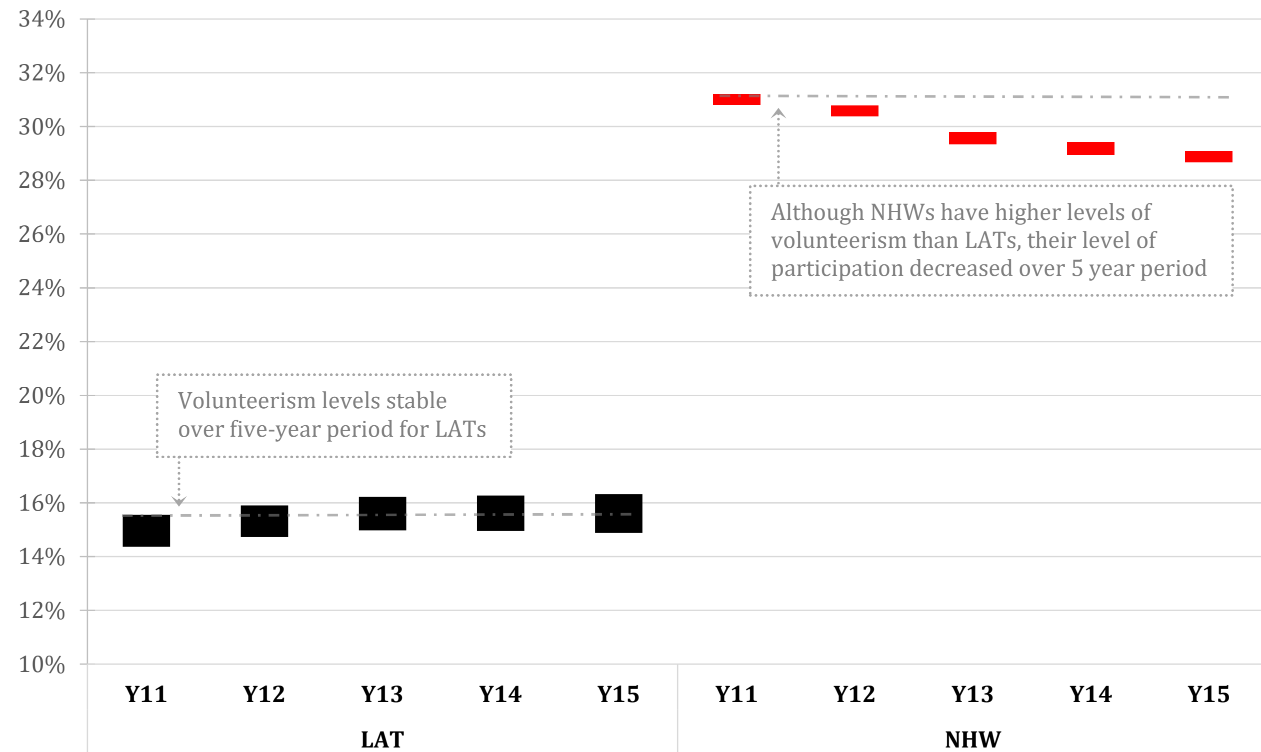
Figure 1

Visual representation of confidence intervals for Hispanics (LAT) and Non-Hispanic-Whites (NHW):Between-group comparisons and temporal trends



Discussion

The study fills a detrimental gap in the volunteerism literature by showing how replicate weights can be used to produce easy-to-understand high-quality statistics when using microdata from the Volunteering Supplement of the CPS. In particular, the analysis found that between-group comparisons suggest NLW had the highest rate of volunteerism than any other race-ethnic group. For the most part, results suggest volunteerism rates may not have differed significantly between NLB and NLO. LAT had the lowest rate of volunteerism of any race-ethnic group.

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Temporal trends suggest volunteerism rate decreased for NLWs and NLOs and did not change for LATs and NLBs.

Albeit novel and valuable for literature on volunteerism, the analysis has several limitations. For example, the analysis did not discuss how data editing protocols (e.g., fixing of erroneous or missing information) or use of proxy respondents may further affect the quality of the estimates and their measures of variance (i.e. MOE). Future studies should explain how much data editing is occurring with survey responses to volunteerism behaviors. Even though advance methods were used to produce direct estimates of variance, further consideration should be given to more complex estimation techniques (Mai, Ha, & Soulakova, 2019). Analysis is also limited in that it did not show how to use replicate weights in regression analysis. Future work should help researchers understand how replicate weights can be used in regression models.

Researchers and administrators should be aware that inferring population characteristics from samples requires great care. Policy makers make decisions based on their belief that data interpreters are providing the correct information. We must remain studious interpreters for data. We are inferring the volunteerism behaviors in the U.S. by using information on less than 0.1% of the population. We must be careful how we discuss population trends. When possible, use replicate weights to create high-quality measures of variance. We must insure we interpret the most truthful version of reality that can be offered by the information gathered from a very small sample of the population. In doing so, we will hopefully increase policy makers' trust in data interpreters.

The current investigation has serious implications for administrators of volunteers. To help their organizations, administrators of volunteers must have a basic understanding of volunteerism patterns in the population. When administrators of volunteers have a clear and true

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picture of what is happening in the volunteer population, they can adjust their recruitment and retention protocols. For example, the present study indicates that organizations that primarily (or exclusively) rely on NLW or NLB volunteers should have their administrators give serious consideration to the fact that rate of participation if declining for both groups. Hence, administrators in these types of organizations should review their recruitment and retention protocols to determine if they need to be redesigned to include new options (e.g., recruiting from other race-ethnic groups). By having a clear and true picture of volunteerism patterns in the population, administrators of volunteers will be able to make the necessary changes to safeguard their organization. This is why administrator of volunteers should continually seek professional development, to expand technical skills and become skilled consumers of complex data. Volunteerism is an important element in the fabric of society. Efforts should continue to explore how it can be expanded in all groups. To do so, we must diligently interpret data with great care.

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Appendix

Statistical program written in SAS 9.4

```
/*
 +-------------------------------------+
 | Programmer: csiordia@gmail.com      |
 |          carlos.siordia@hsc.wvu.edu |
 +-------------------------------------+
 | Specific Aim                        |
 | A.Merge two datasets:               |
 |    1.CPS Sept Volunteer Supplement  |
 |    2.CPS Sept Volunteers Supplement |
 |      Non Response Replicate Weights |
 | B.Produce population estimates      |
 | C.Produce measures of variance      |
 +-------------------------------------+*/
/*
 +------------+
 | First Step |
 +------------+--------------------------+
 | Merge files:                          |
 |  1.Person Level Supplement File       |
 |  2.Person Level Replicate Weight Files |
 |    Note: Only keeps analytic sample    |
 +---------------------------------------+
 | Merge by:                             |
 |  1.Unique household identifier (qstnum)|
 |  2.Unique person identifier (occurnum) |
 |    Note: Both only valid within month  |
 +---------------------------------------+*/
/*
 +-------------+
 | Second Step |
 +-------------+-----+
 | Produce estimates |
 +-------------------+*/
  %LET lok=insert routing of folder containing data files here;
  LIBNAME raw "&lok.";
  OPTIONS MPRINT CLEANUP SYMBOLGEN SPOOL NOFMTERR LINESIZE=200 PAGESIZE=max;
 %MACRO Volunteering;
  %DO i=11 %TO 15 %BY 1;
 /*First step*/
   DATA aa(KEEP=qstnum occurnum pes1 pes2 age pesex prdthsp ptdtrace pwnrwgt);
    SET raw.sep&i.pub;
    q=INPUT(qstnum,8.);DROP qstnum;RENAME q=qstnum;
    o=INPUT(occurnum,8.);DROP occurnum;RENAME o=occurnum;
    IF(("&i."*1)=11)THEN DO;age=(peage*1);END;
        ELSE IF(("&i."*1) ge 12)THEN DO;age=(prtage*1);END;
    RUN;
   PROC SORT DATA=aa;BY qstnum occurnum;RUN;
   DATA bb;
   SET raw.sep&i.rw;
   ARRAY rw {161} repwgt0-repwgt160;
   DO i=1 TO 161;
    rw{i}=(rw{i}/10000);
   END;
   RUN;
   PROC SORT DATA=bb;BY qstnum occurnum;RUN;
   DATA AnalyticSample;
    MERGE aa bb;
    BY qstnum occurnum;
         IF(pes1=1)or(pes2=1)THEN volunteer=1;*Yes;
    ELSE IF(pes1=2)or(pes2=2)THEN volunteer=2;*No;
    ELSE                          volunteer=3;*Missing/other;
         IF(prdthsp ge 1) THEN race=1;*LAT;
    ELSE IF(ptdtrace=1)   THEN race=2;*NLW;
```

```
    ELSE IF(ptdtrace=2)   THEN race=3;*NLB;
    ELSE IF(ptdtrace ge 3)THEN race=4;*NLO;
    ELSE                       race=5;*Missing/other;
    KEEP qstnum occurnum pwnrwgt repwgt0-repwgt160 volunteer race;
    IF(volunteer in(1,2))and(race in(1,2,3,4))THEN OUTPUT;
    RUN;
 /*Second step*/
   %DO x=1 %TO 4 %BY 1;
    %DO j=1 %TO 2 %BY 1;
     PROC MEANS DATA=AnalyticSample SUM NOPRINT;
      WHERE(volunteer=&j.)and(race=&x.);
      VAR pwnrwgt repwgt1-repwgt160;
      OUTPUT OUT=bbb SUM=est rw1-rw160;
      RUN;
     DATA  y&i._v&j._r&x.(KEEP=group race unw wgt lcl ucl cv se moe);
      RETAIN group race unw wgt lcl ucl cv se moe var;
      SET bbb END=eof;
      IF(_n_=1)THEN sdiffsq=0;
      ARRAY repwts {161} est rw1-rw160;
       DO i=2 TO 161 BY 1;
        sdiffsq=(sdiffsq+(repwts{i}-repwts{1})**2);
       END;
      IF eof THEN DO;
       var=((4/160)*sdiffsq);
       se=ROUND(((var)**0.5),.01);
       moe=ROUND((1.96*se),.01);
       cv=ROUND((se/est),.00001);
       lcl=ROUND((est-moe),.1);
       ucl=ROUND((est+moe),.1);
       race=("&x."*1);
       wgt=ROUND(est,.1);
       unw=_freq_;
       LENGTH group $16;
       group="yr&i. v&j. r&x. ";
       OUTPUT;
      END;
     RUN;
    %END;
   %END;
  %END;
 %MEND Volunteering;
 %Volunteering;
/*
 +---------------------------------------------+
 | Print data out to multiple Excel files      |
 | Each XLSX file will have data for one year |
 +---------------------------------------------+*/
 %MACRO sTak;
  %DO j=1 %TO 2 %BY 1;
   %DO i=11 %TO 15 %BY 1;
    DATA y&i._v&j.;SET y&i._v&j._r1-y&i._v&j._r4;RUN;
   %END;
  %END;
  %DO ii=11 %TO 15 %BY 1;
   DATA year&ii.;SET y&ii._v1-y&ii._v2;RUN;
   PROC EXPORT DATA=year&ii. OUTFILE="&lok.\Year&ii..xlsx" DBMS=EXCEL REPLACE;RUN;
  %END;
 %MEND sTak;
 %sTak;
  QUIT;
```