Replicate Variance Estimation in a Two-Phase Sample Design Setting – Simulation Study with 2010 National Survey of College Graduates Data

Michael White[1], Jean Opsomer

U.S. Census Bureau, 4700 Silver Hill Road, Suitland, MD 20746
Colorado State University, Fort Collins, CO 80523

Abstract

The 2010 National Survey of College Graduates (NSCG) selected its sample from 2009 American Community Survey respondents, creating a two-phase sample design. This creates variance estimation complexities when using replication methods, as there are two sample designs to account for. One solution is to create a set of replicates for each sample design phase but this can be unwieldy as it leads to a large number of replicates. Another solution, which we pursued, is to use replicates from the first-phase sample and adjust them to account for the second-phase sample design. In particular, we used a Reweighted Expansion Estimator (REE) that post-stratifies the second-phase sampling weights back to the first-phase estimated totals within each of the second-phase sampling stratum. We conducted a simulation study to evaluate the performance of the REE estimator with different replication methods, including successive difference, grouped-jackknife, and balanced repeated replication. Initial results showed poor performance with some replicate variance estimates due to the inability of the replicates to capture the systematic sample selection used in the second-phase sample design. Accounting for the systematic second-phase sample with post-stratification resulted in good performance for the REE estimator with all the replication methods and the successive difference replication method was ultimately chosen as the 2010 NSCG production method.

Key Words: variance estimation, replication, two-phase sample design, NSCG, ACS, simulation

1. Introduction

The National Survey of College Graduates (NSCG) is a longitudinal survey that collects information on employment, educational, and demographic characteristics of the college-educated science and engineering (S&E) workforce in the United States. The U.S. Census Bureau conducts the NSCG on behalf of the National Science Foundation (NSF). The 2010 NSCG selected its sample using a dual frame design. One frame included respondents to the 2008 NSCG and 2008 National Survey of Recent College Graduates (NSRCG) and is referred to as the “old” cohort, and the other frame included respondents

[1] Disclaimer: Any views expressed are those of the authors and not necessarily those of the U.S. Census Bureau or Colorado State University

to the 2009 American Community Survey (ACS) and is referred to as the "new" cohort[2]. Cases were eligible for the "new" cohort sampling frame if they had responded to the 2009 ACS, reported obtaining at least a Bachelor's degree, were less than 76 years of age, and were noninstitutionalized[3]. From a frame of 855,402 eligible cases, 65,195 "new" cohort sample cases were selected. This paper will only discuss variance estimation for the "new" cohort portion of the 2010 NSCG as this is where the two-phase sample design concerns arise.

It is common to use two-phase sampling to observe auxiliary variables in the first-phase sample and then use those auxiliary variables to stratify the second-phase sample. This was the case with the 2010 NSCG as the sampling frame was stratified using occupation field, educational attainment, and demographic variables obtained in the 2009 ACS. An issue arises with variance estimation in this two-phase sample setting because the usual replication-based variance estimation methods cannot be directly applied in the two-phase context. In fact, the literature on replication methods for two-phase sampling is surprisingly sparse, with only a small number of authors attempting to tackle this issue. Even though unbiased linearized variance estimators exist, the conditional probabilities of selection and asymptotic conditions of the two samples make the theory messy in developing replicate variance estimators. In other words, it is difficult to create replicates that can account for both the first and second-phase sample and so proposed replicate variance estimators are biased. Our previous paper (White and Opsomer (2011)) discussed the existing literature on replication in two-phase samples, discussed our proposed replicate variance estimation approach for the 2010 NSCG, and provided preliminary results using our proposed approach. This paper is a continuation of our previous paper and will discuss the results of a simulation study that assessed the performance of replicates using the Reweighted Expansion Estimator (REE) in the 2010 NSCG.

2. Background

In our previous paper (White and Opsomer (2011)), we discussed the existing literature on replication in two-phase samples, proposed replicate estimators for use in the 2010 NSCG, detailed the creation of five different sets of replicates for comparison, and described a simulation study to evaluate the replicate estimators and replication methods. We will summarize this information and then go on to show the results of the simulation study that evaluated the replicate estimators and replication methods.

In practice, two common estimators are used in two-phase sampling: the double expansion estimator (DEE) and reweighted expansion estimator (REE) (Kott and Stukel

[2] Historically, the NSCG sample was selected once a decade from the decennial census long form respondents. In 2010, the Census Bureau discontinued the long form, so the NSF switched to using the American Community Survey (ACS) as a sampling frame for the NSCG.

[3] There are other minor eligibility criteria for the "new" cohort sampling frame. For details on all the eligibility criteria, see Finamore and Hall (2010).

(1997)). These estimators are defined under ideal conditions, i.e. full response, no frame errors, etc. The DEE is defined as

$$\hat{t}_{ys} = \sum_{s} \frac{y_k}{\pi_{ak}\pi_{k|s_a}} \tag{1}$$

where s includes the second-phase sample cases, y_k is the estimate of interest, $\pi_{ak}$is the first-phase inclusion probability, and $\pi_{k|s_a}$is the conditional second-phase inclusion probability. The REE is defined as

$$\hat{t}_{ys,ratio} = \sum_{g=1}^{G} \sum_{s_{ag}} \frac{1}{\pi_{ak}} \frac{\sum_{s_g} \frac{y_k}{\pi_{ak}\pi_{k|s_a}}}{\sum_{s_g} \frac{1}{\pi_{ak}\pi_{k|s_a}}} \tag{2}$$

where g indexes the second-phase sampling strata, s_{ag} is the sample of the first-phase cases in stratum g, s_g the sample of the second-phase cases in stratum g, and the other terms are as defined previously. Unlike the DEE, this estimator post-stratifies the weights back to the estimated totals within each stratum.

Kott and Stukel (1997) examined jackknife replication with the DEE and REE in a two-phase sample design. They conducted a simulation study and found that the REE estimator was more efficient than the DEE estimator. Kim, Navarro, and Fuller (2006) theoretically discuss replicate variance estimation with a general replication method using the DEE and REE in a two-phase sample. In particular, they propose a consistent variance estimator that is applicable for both the DEE and REE given a consistent first-phase replicate variance estimator. Both of these papers analyzed sample designs that use stratified simple random sampling (SRS) in the second-phase sample. The primary challenge with directly applying their results to the 2010 NSCG is that the 2010 NSCG selected some of its sample using stratified systematic SRS and some of its sample using stratified systematic probability proportional to size (PPS) sampling. The unequal probabilities of selection in the second-phase sample require adjustments to the DEE and REE replicate estimators discussed in the above papers.

NOTE: Although the DEE replicate estimator was initially considered for evaluation, we dropped it from further research. This was due to the efficiency advantage of the REE and also due to difficulties using the estimator with unequal selection probabilities in the second-phase sample. See Opsomer (2011) for more details on the complications with the DEE replicate estimator. The remainder of this paper will only deal with the REE replicate estimator.

In response to the 2010 NSCG sample design, we propose the following replicate variance estimator for the REE estimator

$$\hat{V}_{ratio} = \sum_{r=1}^{R} c_r (\hat{t}_{ys,ratio}^{(r)} - \hat{t}_{ys,ratio})^2 \tag{3}$$

where c_r is a constant that depends on the replication method, R is the number of replicates, and the REE replicate estimator $\hat{t}_{ys,ratio}^{(r)}$ is defined as

$$t_{ys,ratio}^{(r)} = \sum_{g=1}^{G} \sum_{s_{ag}} w_{ak}^{(r)} \frac{\sum_{s_g} \frac{w_{ak}^{(r)} y_k}{\pi_{k|s_a}}}{\sum_{s_g} \frac{w_{ak}^{(r)}}{\pi_{k|s_a}}} \tag{4}$$

where $w_{ak}^{(r)}$ is the first-phase replicate weight and the other terms are as defined previously. We evaluated the replicate variance estimator (3) by conducting a simulation study that will be described in Section 3.

In addition to investigating an appropriate estimator to use for the 2010 NSCG, we also evaluated different variance replication methods. The ACS uses the Successive Difference Replication (SDR) method (Fay and Train (1995)). The sample design for the ACS is an unequal-probability, stratified systematic sample of U.S. households with independent samples of households selected within each county in the U.S. and Puerto Rico. The systematic sample selection is made after sorting census blocks geographically within each county. SDR replicates are assigned within counties using this sort order.

The SDR method was designed to be used with systematic samples for which the sort order of the sample is informative, which is the case with ACS's geographic sort. However, it is unclear whether the ACS's SDR replicate weights are suitable for the 2010 NSCG since the 2010 NSCG stratifies by demographics, not geography. Additionally, it is unclear how robust SDR is to large sample reductions that occur in the 2010 NSCG two-phase sample design. Therefore, it is possible the Balanced Repeated Replication (BRR) or delete-a-group Jackknife Replication (JKR) method may be more appropriate for the 2010 NSCG.

In response to the concern with SDR, we created BRR and JKR replicates as a comparison against the SDR replicates. We created the BRR and JKR replicates by assigning pseudo-strata for each of these methods in two different ways to create four additional replicate methods. The first way we assigned pseudo-strata paid attention to the geographic *sort* of the ACS. These replicates are referred to as BRR-1 and JKR-1 throughout this document. The second way we assigned pseudo-strata to create BRR and JKR replicates paid attention to the geographic *strata* (counties) used in the ACS. These replicates are referred to as BRR-2 and JKR-2 throughout this document. For more detailed information on the creation of these replicates, see the appendix.

The next section will describe the simulation study conducted to evaluate the REE estimator and the five replication methods: SDR, BRR-1, BRR-2, JKR-1, JKR-2.

3. Simulation Study

3.1 Simulation Study Metrics

Two-phase samples potentially induce bias in replication-based variance estimators; therefore, the primary metric of interest in the simulation study is the bias of the variance estimators. Because we only have a single realization of ACS, the first-phase sample, we cannot directly compare the bias of variance estimators with full simulation-based variances. Instead, we derived an approximation that uses simulation of the second-phase sample from a fixed first-phase to provide insight on the bias of the variance estimators. This is a partial simulation since we treat the first-phase sample as fixed and only simulate the second-phase sample.

The following equations will consider the REE estimator. The variance estimate obtained by using any of the five replication methods will be generically denoted by $\hat{V}$. The ACS sample is denoted by s_a. The true variance of $\hat{t}_{ys}$ is

$$\mathrm{Var}(\hat{t}_{ys,ratio}) \; = \; \mathrm{E}(\mathrm{Var}(\hat{t}_{ys,ratio}|s_a)) + \mathrm{Var}(\mathrm{E}(\hat{t}_{ys,ratio}|s_a)) \qquad (5)$$

and $\hat{V}$ is a proposed estimator of Var($\hat{t}_{ys,ratio}$). We are interested in evaluating whether Bias($\hat{V}$)=E($\hat{V}$)-Var($\hat{t}_{ys,ratio}$) is sufficiently close to 0. To evaluate the bias of $\hat{V}$ using a single realization of the ACS, we will use the "conditional estimator"[4]

$$\hat{B}_{s_a} \; = \; \mathrm{E}^*\left(\hat{V}_{ratio}|s_a\right) - \mathrm{Var}^*\left(\hat{t}_{ys,ratio}|s_a\right) - \hat{V}_{\mathrm{a}} \qquad (6)$$

where E* and Var* denote the moments are approximated via simulation, and $\hat{V}_{\mathrm{a}}$ is the chosen replication variance estimator (SDR, BRR-1, BRR-2, JKR-1, JKR-2) applied to the first-phase.

The simulated estimates are calculated by taking 1,000 second-phase samples of the 2010 NSCG from the first-phase ACS sample. The first term in (6) is calculated by creating a set of replicate weights for each simulated second-phase sample, calculating a replicate variance estimate for each second-phase sample, and then averaging the replicate variance estimates across all second-phase samples. The second term in (6) is calculated by taking the variance of the simulated estimate across all 1,000 second-phase samples. The third term in (6) is calculated as the replicate variance of the estimate using the single realization of the first-phase sample.

Because of the large size of the ACS relative to the NSCG, we expect that using $\hat{B}_{s_a}$ instead of the true bias is reasonable as a way to evaluate the replication methods. However, because it is not the true bias, it is still subject to variability and our interpretation of the estimated bias takes this into consideration. Therefore, we looked for large and consistent differences between the estimators across different variables and

[4] See Opsomer (2010b) for a derivation and justification for this formula.

domains. An additional metric we examined was the relative bias of the point estimates using the REE estimator.

As a reminder, the evaluation will only focus on determining which replication method performs best using the *REE* as the replicate estimator.

3.2 Simulation Study Results

The relative bias of the replicate variance estimates was calculated as the bias of the replicate variance estimate divided by the estimate of the true variance. Table 1 (see appendix for tables) shows the relative bias of the five replication methods for proportion estimates of several ACS variables[5]. Also shown is the relative bias of the point estimates. The figures in this table indicate the following main results:

- All five replication methods perform similarly with respect to relative bias
- The relative bias of the replicate variances are generally small (<10%)
- The major exceptions to the small relative bias are large overestimation of variance for estimates of gender, age group, and race
- The relative bias of variance for estimates of highest degree, ethnicity (Hispanic), and occupation are zero or close to zero
- The point estimates have very small relative bias (<1%)

The good news is that the REE replicate estimator performs well for most of the estimates. There is even zero (or near zero) relative bias on the variance estimates for highest degree, ethnicity, and occupation. This is because these variables are used to form the second-phase sampling cells. Since the REE replicate estimator ensures the second-phase sampling cell totals sum to the first-phase frame totals there is no second-phase variance introduced on the sampling cell variables. This removes the replicate variance bias issues associated with two-phase samples for these variables. None of the five replication methods stands out as better than the others with respect to the relative bias of the variance estimates.

The bad news is that there is large variance overestimation for gender, age group, and race. The commonality amongst these variables is that they were all used to sort the second-phase NSCG sample before systematically selecting the sample. The systematic sample selection with sorting results in an implicit stratification that reduces the variance on the sort variables. However, the REE replicate estimator is unable to capture this aspect of the second-phase sample design and thus leads to overestimation of variance.

We also examined estimation for subgroups of interest to NSCG data analysts and found significant variance overestimation for subgroups that relate to the sample sort variables. Table 2 shows the relative bias of the REE replicate estimator for females and significant bias is found across a range of variables.

---

[5] Estimates of totals were also examined, but since the results closely match the results for proportions the tables for totals are excluded from this paper.

Our solution to this variance overestimation was to post-stratify the simulated NSCG samples by breaking out the sampling cells into a cross of gender, age group, and race[6]. In doing so, we made the implicit stratification from the sort more explicit and hoped to have the replicate weights capture this aspect of the sample design. The cross of these three variables resulted in a potential breakout of each sampling cell of eight levels. Since some of these broken-out cells contained frame cases but little or no sample cases, collapsing was performed[7]. The sample totals were then post-stratified to the first-phase frame totals within each broken-out sampling cell. This process is similar to how we created the original REE replicate weights using formula (4), except the value of g was the broken-out sampling cell instead of the original sampling cell. Due to limited resources, we only conducted the post-stratification on the SDR, BRR-1, and JKR-1 replicates. We do not expect dropping the BRR-2 and JKR-2 replicates from the post-stratification analysis will affect results since all five replication methods appear to perform similarly. The results of this post-stratification on the simulated samples are shown in Tables 3 and 4.

Table 3 indicates that post-stratification was a success. The relative bias of the REE replicate variance estimates for gender went from the 1300% range before post-stratification to the 45% range after post-stratification. Similar large reductions were seen in the relative bias for age group and race estimates. Large biases remain for estimates of Native Hawaiians/Pacific Islanders but this is not a major concern since this group represents only 0.1% of the NSCG target population. Table 4 indicates success in significantly reducing the relative biases of the variance estimates for subgroup estimates of females. The average relative bias for female variance estimates went from around 200% to around 10%.

The JKR-1 replicates did not perform as well as the SDR and BRR-1 replicates under this post-stratification scheme with relative biases about two to three times as large as the SDR and BRR-1 relative biases.

4. Conclusions

After a suitable post-stratification adjustment, our proposed REE replicate estimator performs well for NSCG variance estimation needs. The estimator appropriately addresses replicate variance bias concerns with two-phase samples and accurately captures the variance at each sampling phase. The post-stratification using the sample

[6] Gender is a two-level variable (male/female) and age group is a two-level variable (less than 40 years old/40 years or older). When race was used as a sort variable in sample selection it included six levels but for post-stratification we reduced it to a two-level (black/non-black) variable to avoid too fine of a breakout of sampling cell.

[7] The same collapsing of the post-stratification cells was used for all 1,000 simulated samples for operational simplicity. However, this simplification resulted in some simulated samples having zero sample cases in some post-stratification cells and thus led to small levels of bias in the estimation. We do not think this small level of bias affected the results of this research.

sort variables was necessary to address bias concerns and future users of the REE replicate estimator should be careful when their second-phase sample uses sorted systematic sampling. Small overestimation of variance remains but this leads to more conservative variance estimation which is preferable to underestimating the variance.

Although we had some concerns with SDR's robustness to large sample reductions, we did not find this to be an issue. In fact, we found all replication methods produced reasonable results with some small concerns with the performance of jackknife replication under post-stratification. We have decided to use SDR as our replication method since ACS staff creates SDR replicates for use in their survey.

5. References

Fay, Robert, and George Train. (1995). "Aspects of Survey and Model-Based Postcensal Estimation of Income and Poverty Characteristics for States and Counties." Proceedings of the Section on Government Statistics, American Statistical Association, Alexandria, VA, pp. 154-159.

Finamore, John and David Hall, "Eligibility and Stratification Definitions for the 2010 National Survey of College Graduates Sample Selection (Document # NSCG10-SAMP-2)," Census Bureau Memorandum for Landman from Killion, October, 2010.

Kim, J.K., A. Navarro, and W.A. Fuller (2006). "Replication variance estimation for two-phase stratified sampling." Journal of the American Statistical Association 101 (473), 312-320

Kott, P. (2001) "The Delete-a-Group Jackknife" Journal of Official Statistics, Vol. 17, No.4, pp.521-526

Kott, P. S. and Stukel, D. M. (1997). "Can the jackknife be used with a two-phase sample?" Survey Methodology 23, 81-89

Opsomer, J.D. (2010a). "Two-phase variance estimation for the National Survey of College Graduates." Unpublished manuscript, May 4, 2010.

Opsomer, J.D. (2010b)."Comments on December 7 NSCG memo." Unpublished manuscript, December 13, 2010.

Opsomer, J.D. (2011)."Reply to August 11 Question." Unpublished manuscript, August 12, 2011.

White, Michael and Jean D. Opsomer (2011). "Variance Estimation Issues in the 2010 NSCG Two-Phase Sample Design," JSM Proceedings; Section on Survey Research Methods, 3987-4000

Wolter, K. M. (2007). Introduction to Variance Estimation (2nd Edition), Springer, New York.

Appendix

Creation of the Alternative Sets of Replicate Weights

In response to the concern with SDR, we created BRR and JKR replicates as a comparison against the SDR replicates. We created the BRR and JKR replicates by assigning pseudo-strata for each of these methods in two different ways to create four additional replicate methods. The pseudo-strata were first assigned in a way to mimic the original assignment of SDR replicate factors. The SDR replicate factors were assigned using the systematic geographic sort of the sample, which implicitly creates 'pseudo-strata' of pairs of sampling units. Using the sort order of the original SDR replicate factors, consecutive pairs of cases were therefore assigned to the BRR two-per-stratum pseudo-strata. Because the number of pseudo-strata greatly exceeded the dimension of the Hadamard matrix, *partial balancing* was used to create the replicates (see Wolter, 2007, Ch. 3.6). This means that each row of the Hadamard was assigned to a large number of pairs of cases, which can be thought of as creating 'pseudo-PSUs' within larger pseudo-strata that contain repeated pairs of cases. See Figure 1 for an illustration of how the pseudo-strata and 'pseudo-PSUs' were assigned. For the JKR replicates, the cases in each of these larger pseudo-strata were randomly assigned to 80 groups. By balancing the jackknife groups across the SDR sort order in this manner, the replication method is expected to more closely reflect the geographic balancing of the original ACS sampling design. The replicates created with these pseudo-strata were referred to as BRR-1 and JKR-1 throughout this paper.

Figure 1. Example of Assignment of Pseudo-Strata and PSUs

SDR Sort Order	BRR-1 and JKR-1 Pseudo-Strata	BRR-1 'Pseudo-PSU'
1	1	1
2	1	2
3	2	3
4	2	4
…	…	…
155	78	155
156	78	156
157	1	1
158	1	2
…	…	…

The first method for assigning pseudo-strata mimicked the SDR replicate factor assignment to create an apples-to-apples comparison amongst the methods and paid particular attention to the systematic geographic sort of the sample. However, if the SDR replicates did not exist then it would make more sense for the BRR and JKR replicates to be constructed in a way that more closely reflects the ACS's overall geographic stratification. Therefore, the pseudo-strata were next assigned using geography in two ways. For the BRR replicates, most states were assigned their own pseudo-stratum but the larger states were broken down into two or more pseudo-strata with similar sized counties in each pseudo-stratum. Within these pseudo-strata, the cases were sorted the same way used to assign the SDR replicates and the cases were then systematically assigned to two 'pseudo-PSUs'. The first case in each consecutive pair of cases was assigned to the first 'pseudo-PSU' and the second case was assigned to the second 'pseudo-PSU'. The 'pseudo-PSU' assignment was randomly switched in about half of the pairs of cases to prevent issues that could arise if there were cycles in the sort order. The effect of this 'pseudo-PSU' assignment is that each 'pseudo-PSU' is geographically representative of each pseudo-stratum. For the JKR replicates, each county was assigned to its own strata, reflecting the actual strata used by the ACS. The cases in each stratum were then randomly assigned to 80 groups. Since some counties contained less than 80 sample cases, an adjusted delete-a-group Jackknife method was used to assign replicate factors (Kott (2001)). These replicates created using geography as pseudo-strata/strata were referred to as BRR-2 and JKR-2 throughout this paper.

Appendix

Table 1. Relative Bias of REE Replicate Variance Estimators

Variable	Value	Frame Estimate	Expected Sample Estimate	Point Estimate Relative Bias	SDR Relative Bias	BRR-1 Relative Bias	BRR-2 Relative Bias	JKR-1 Relative Bias	JKR-2 Relative Bias
Covered by health insurance	Yes	93.1%	93.1%	0.01%	-4.02%	-3.76%	-2.59%	-2.51%	-1.75%
	No	6.9%	6.9%	-0.16%	-4.02%	-3.76%	-2.59%	-2.51%	-1.75%
In poverty	Yes	4.4%	4.4%	-0.02%	2.18%	3.10%	4.88%	5.11%	4.36%
	No	95.6%	95.6%	0.00%	2.18%	3.10%	4.88%	5.11%	4.36%
Unemployed	Yes	3.9%	3.9%	0.08%	-11.31%	-9.93%	-12.74%	-9.48%	-8.13%
	No	96.1%	96.1%	0.00%	-11.31%	-9.93%	-12.74%	-9.48%	-8.13%
Urban/Rural	Urban	81.4%	81.4%	0.00%	1.08%	-0.09%	-0.31%	1.65%	2.45%
	Rural	18.6%	18.6%	0.01%	1.08%	-0.09%	-0.31%	1.65%	2.45%
Marital status	Married	64.7%	64.8%	0.03%	6.56%	6.01%	7.01%	8.58%	7.77%
	Widowed	1.7%	1.7%	-0.06%	-2.96%	-1.53%	-2.45%	-0.96%	0.83%
	Divorced	9.4%	9.4%	-0.02%	3.39%	5.30%	4.86%	7.05%	7.97%
	Separated	1.2%	1.2%	0.00%	-0.96%	0.15%	0.36%	0.37%	1.46%
	Never married	23.0%	23.0%	-0.09%	12.66%	14.12%	13.78%	16.15%	15.82%
Highest degree	Bachelor/Professional	71.4%	71.4%	0.00%	0.00%	0.00%	0.00%	-0.15%	-0.30%
	Master's	24.8%	24.8%	0.00%	0.00%	0.00%	0.00%	0.07%	0.12%
	Doctorate	3.8%	3.8%	0.00%	0.00%	0.00%	0.00%	0.17%	0.22%
Disabled	Yes	5.3%	5.3%	0.00%	5.83%	6.59%	6.49%	7.73%	8.64%
	No	94.7%	94.7%	0.00%	5.83%	6.59%	6.49%	7.73%	8.64%
Hispanic	Yes	7.0%	7.0%	0.00%	0.00%	0.00%	0.00%	0.67%	-0.10%
	No	93.0%	93.0%	0.00%	0.00%	0.00%	0.00%	0.67%	-0.10%
Race	White	80.8%	80.8%	0.00%	15.54%	16.38%	14.84%	15.51%	16.25%
	Black	7.7%	7.7%	0.00%	48.72%	56.87%	46.16%	44.23%	60.11%
	Asian	8.9%	8.9%	0.00%	-1.49%	-1.47%	-1.19%	-0.72%	-0.78%
	AIAN	0.8%	0.8%	0.12%	40.96%	45.29%	47.73%	49.40%	51.05%
	NHPI	0.1%	0.1%	-0.67%	154.61%	156.79%	160.96%	180.79%	185.78%
	Other	1.6%	1.6%	-0.12%	7.91%	7.52%	6.07%	8.76%	9.40%
U.S. citizen at birth	Yes	84.7%	84.7%	0.00%	-1.79%	-1.19%	-0.77%	-0.15%	1.19%
	No	15.3%	15.3%	-0.03%	-1.79%	-1.19%	-0.77%	-0.15%	1.19%
S&E Degree	Yes	46.0%	46.0%	0.00%	-12.83%	-13.36%	-11.54%	-11.09%	-10.51%
	No	54.0%	54.0%	0.00%	-12.83%	-13.36%	-11.54%	-11.09%	-10.51%
Gender	Male	48.2%	48.2%	0.00%	1329.01%	1301.23%	1439.93%	1313.22%	1484.99%
	Female	51.8%	51.8%	0.00%	1329.01%	1301.23%	1439.93%	1313.22%	1484.99%
Age group	0-39	36.5%	36.5%	-0.02%	542.91%	573.30%	559.73%	604.60%	587.17%
	40+	63.5%	63.5%	0.01%	542.91%	573.30%	559.73%	604.60%	587.17%
Occupation	Comp/Math	3.9%	3.9%	0.00%	0.00%	0.00%	0.00%	0.03%	-0.01%
	Life Sciences	0.5%	0.5%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
	Physical Sciences	0.7%	0.7%	0.00%	0.00%	0.00%	0.00%	0.00%	0.01%
	Social Sciences	0.7%	0.7%	0.00%	0.00%	0.00%	0.00%	0.03%	0.01%
	Engineering	2.7%	2.7%	0.00%	0.00%	0.00%	0.00%	0.38%	0.24%
	S&E-R Health	8.8%	8.8%	0.00%	0.00%	0.00%	0.00%	0.00%	0.04%
	S&E-R Non-Health	6.1%	6.1%	0.00%	0.00%	0.00%	0.00%	-0.06%	0.02%
	Teachers	4.2%	4.2%	0.00%	0.00%	0.00%	0.00%	0.02%	0.05%
	Non S&E	62.9%	62.9%	0.00%	0.00%	0.00%	0.00%	0.02%	-0.14%
	Not Working	9.5%	9.5%	0.00%	0.00%	0.00%	0.00%	0.63%	-0.25%
		Average Relative Bias:		-0.02%	90.62%	91.30%	96.92%	94.31%	102.10%

AIAN - American Indian/Alaskan Native
NHPI - Native Hawaiian/Pacific Islander
S&E - Science and Engineering

Appendix

Table 2. Relative Bias of REE Replicate Variance Estimators – Females

Variable	Value	Frame Estimate	Expected Sample Estimate	Point Estimate Relative Bias	SDR Relative Bias	BRR-1 Relative Bias	BRR-2 Relative Bias	JKR-1 Relative Bias	JKR-2 Relative Bias
Covered by health insurance	Yes	93.5%	93.5%	0.01%	1.89%	2.59%	5.62%	4.37%	5.93%
	No	6.5%	6.5%	-0.16%	1.89%	2.59%	5.62%	4.37%	5.93%
In poverty	Yes	4.8%	4.8%	-0.02%	2.16%	2.73%	4.44%	6.29%	4.10%
	No	95.2%	95.2%	0.00%	2.16%	2.73%	4.44%	6.29%	4.10%
Unemployed	Yes	3.7%	3.7%	0.08%	14.07%	16.11%	14.32%	18.38%	17.69%
	No	96.4%	96.3%	0.00%	14.07%	16.11%	14.32%	18.38%	17.69%
Urban/Rural	Urban	81.2%	81.2%	0.00%	1.89%	1.54%	2.82%	4.12%	5.11%
	Rural	18.8%	18.8%	0.01%	1.89%	1.54%	2.82%	4.12%	5.11%
Marital status	Married	61.7%	61.7%	0.03%	8.39%	8.39%	9.07%	10.97%	9.08%
	Widowed	2.5%	2.5%	-0.06%	-3.48%	-2.19%	-1.92%	-1.25%	0.64%
	Divorced	11.0%	11.0%	-0.02%	0.85%	3.13%	1.38%	4.02%	5.47%
	Separated	1.4%	1.4%	0.00%	-0.97%	-0.01%	0.57%	1.63%	1.26%
	Never married	23.4%	23.4%	-0.09%	18.55%	18.44%	17.35%	21.29%	20.40%
Highest degree	Bachelor/Professional	70.8%	70.8%	0.00%	765.83%	770.70%	870.47%	853.65%	809.87%
	Master's	26.4%	26.4%	0.00%	789.06%	819.70%	1069.32%	892.13%	867.99%
	Doctorate	2.8%	2.8%	0.00%	298.36%	280.66%	315.27%	322.84%	357.20%
Disabled	Yes	5.1%	5.1%	0.00%	125.42%	128.05%	128.92%	129.30%	130.21%
	No	94.9%	94.9%	0.00%	125.42%	128.05%	128.92%	129.30%	130.21%
Hispanic	Yes	7.4%	7.4%	0.00%	658.67%	769.49%	1119.86%	914.14%	821.11%
	No	92.6%	92.6%	0.00%	658.67%	769.49%	1119.86%	914.14%	821.11%
Race	White	79.6%	79.6%	0.00%	209.76%	216.57%	204.41%	208.37%	218.30%
	Black	8.9%	8.9%	0.00%	379.22%	405.69%	311.92%	384.78%	405.44%
	Asian	8.7%	8.7%	0.00%	478.69%	531.79%	588.00%	524.05%	538.56%
	AIAN	0.9%	0.9%	0.12%	157.53%	169.62%	173.88%	171.06%	192.00%
	NHPI	0.1%	0.1%	-0.67%	176.17%	182.38%	182.93%	211.91%	206.17%
	Other	1.7%	1.7%	-0.12%	8.60%	11.12%	10.11%	11.08%	12.57%
U.S. citizen at birth	Yes	85.3%	85.3%	0.00%	77.11%	80.13%	81.19%	80.58%	80.44%
	No	14.7%	14.7%	-0.03%	77.11%	80.13%	81.19%	80.58%	80.44%
S&E Degree	Yes	41.3%	41.3%	0.00%	229.95%	238.90%	214.61%	232.07%	237.29%
	No	58.7%	58.7%	0.00%	229.95%	238.90%	214.61%	232.07%	237.29%
Gender	Male	-	-	-	-	-	-	-	-
	Female	100.0%	100.0%	0.00%	-	-	-	-	-
Age group	0-39	39.3%	39.3%	-0.02%	628.70%	681.32%	679.67%	695.42%	689.21%
	40+	60.7%	60.7%	0.01%	628.70%	681.32%	679.67%	695.42%	689.21%
Occupation	Comp/Math	2.1%	2.1%	0.00%	282.57%	269.52%	312.37%	305.57%	235.17%
	Life Sciences	0.4%	0.4%	0.00%	64.03%	65.61%	60.80%	68.97%	75.15%
	Physical Sciences	0.5%	0.5%	0.00%	60.19%	80.96%	70.82%	61.24%	58.04%
	Social Sciences	0.8%	0.8%	0.00%	79.62%	71.22%	87.54%	101.48%	74.00%
	Engineering	0.7%	0.7%	0.00%	226.06%	154.39%	202.34%	157.51%	208.15%
	S&E-R Health	11.6%	11.6%	0.00%	259.74%	286.44%	249.37%	288.61%	317.10%
	S&E-R Non-Health	5.9%	5.9%	0.00%	243.88%	241.43%	233.88%	237.59%	248.77%
	Teachers	4.4%	4.4%	0.00%	176.89%	212.50%	213.29%	182.31%	210.95%
	Non S&E	61.4%	61.4%	0.00%	542.83%	671.41%	561.65%	553.73%	579.64%
	Not Working	12.1%	12.1%	0.00%	517.71%	702.18%	579.69%	619.91%	550.16%
		Average Relative Bias:		-0.02%	219.52%	238.41%	257.80%	246.73%	242.48%

AIAN - American Indian/Alaskan Native
NHPI - Native Hawaiian/Pacific Islander
S&E - Science and Engineering

Appendix

Table 3. Relative Bias of REE Replicate Variance Estimators after Post-Stratification Adjustment

Variable	Value	Frame Estimate	Expected Sample Estimate	Point Estimate Relative Bias	SDR Relative Bias	BRR-1 Relative Bias	JKR-1 Relative Bias
Covered by health insurance	Yes	93.1%	93.2%	0.01%	-5.45%	-4.61%	-0.46%
	No	6.9%	6.8%	-0.16%	-5.45%	-4.61%	-0.46%
In poverty	Yes	4.4%	4.4%	-0.02%	0.88%	3.10%	8.81%
	No	95.6%	95.6%	0.00%	0.88%	3.10%	8.81%
Unemployed	Yes	3.9%	3.9%	0.08%	-13.37%	-11.62%	-8.60%
	No	96.1%	96.1%	0.00%	-13.37%	-11.62%	-8.60%
Urban/Rural	Urban	81.4%	81.4%	0.00%	0.21%	-0.50%	2.24%
	Rural	18.6%	18.6%	0.01%	0.21%	-0.50%	2.24%
Marital status	Married	64.7%	64.8%	0.03%	0.68%	1.39%	5.07%
	Widowed	1.7%	1.7%	-0.06%	-4.96%	-3.62%	-1.07%
	Divorced	9.4%	9.4%	-0.02%	0.36%	2.03%	5.81%
	Separated	1.2%	1.2%	0.00%	-2.64%	-0.90%	1.90%
	Never married	23.0%	22.9%	-0.09%	-1.53%	0.03%	3.48%
Highest degree	Bachelor/Professional	71.4%	71.5%	0.00%	-1.64%	-2.95%	12.35%
	Master's	24.8%	24.7%	0.00%	-1.43%	-2.14%	9.66%
	Doctorate	3.8%	3.8%	0.00%	-10.24%	-8.09%	24.90%
Disabled	Yes	5.3%	5.3%	0.00%	3.49%	5.51%	13.13%
	No	94.7%	94.7%	0.00%	3.49%	5.51%	13.13%
Hispanic	Yes	7.0%	7.0%	0.00%	-3.95%	-3.57%	15.68%
	No	93.0%	93.0%	0.00%	-3.95%	-3.57%	15.68%
Race	White	80.8%	80.8%	0.00%	0.40%	1.88%	8.77%
	Black	7.7%	7.7%	0.00%	4.99%	8.46%	15.45%
	Asian	8.9%	8.9%	0.00%	-3.76%	-3.41%	10.22%
	AIAN	0.8%	0.8%	0.12%	29.60%	36.41%	67.12%
	NHPI	0.1%	0.1%	-0.67%	144.07%	146.80%	224.81%
	Other	1.6%	1.6%	-0.12%	4.03%	5.78%	11.97%
U.S. citizen at birth	Yes	84.7%	84.7%	0.00%	-2.84%	-1.67%	4.79%
	No	15.3%	15.3%	-0.03%	-2.84%	-1.67%	4.79%
S&E Degree	Yes	46.0%	46.0%	0.00%	-13.24%	-13.94%	-7.87%
	No	54.0%	54.0%	0.00%	-13.24%	-13.94%	-7.87%
Gender	Male	48.2%	48.2%	0.00%	46.20%	43.37%	55.70%
	Female	51.8%	51.8%	0.00%	46.20%	43.37%	55.70%
Age group	0-39	36.5%	36.5%	-0.02%	0.67%	1.53%	15.05%
	40+	63.5%	63.5%	0.01%	0.67%	1.53%	15.05%
Occupation	Comp/Math	3.9%	3.9%	0.00%	-0.18%	0.00%	-0.08%
	Life Sciences	0.5%	0.5%	0.00%	0.07%	0.08%	0.34%
	Physical Sciences	0.7%	0.7%	0.00%	-0.25%	-0.19%	2.02%
	Social Sciences	0.7%	0.7%	0.00%	-0.15%	-0.02%	4.03%
	Engineering	2.7%	2.7%	0.00%	0.08%	0.02%	2.21%
	S&E-R Health	8.8%	8.8%	0.00%	-2.20%	-4.11%	7.23%
	S&E-R Non-Health	6.1%	6.1%	0.00%	-0.61%	-0.65%	5.89%
	Teachers	4.2%	4.2%	0.00%	-0.07%	-0.65%	4.49%
	Non S&E	62.9%	62.9%	0.00%	-1.10%	-1.10%	5.59%
	Not Working	9.5%	9.5%	0.00%	-1.50%	-2.15%	14.71%
		Average Relative Bias:		-0.02%	4.03%	4.73%	14.63%

AIAN - American Indian/Alaskan Native
NHPI - Native Hawaiian/Pacific Islander
S&E - Science and Engineering

Appendix

Table 4. Relative Bias of REE Replicate Variance Estimators after Post-Stratification Adjustment – Females

Variable	Value	Frame Estimate	Expected Sample Estimate	Point Estimate Relative Bias	SDR Relative Bias	BRR-1 Relative Bias	JKR-1 Relative Bias
Covered by health insurance	Yes	93.5%	93.5%	0.01%	-0.90%	0.51%	5.03%
	No	6.5%	6.5%	-0.16%	-0.90%	0.51%	5.03%
In poverty	Yes	4.8%	4.8%	-0.02%	0.42%	2.01%	7.81%
	No	95.2%	95.2%	0.00%	0.42%	2.01%	7.81%
Unemployed	Yes	3.7%	3.7%	0.08%	12.53%	15.11%	19.94%
	No	96.4%	96.3%	0.00%	12.53%	15.11%	19.94%
Urban/Rural	Urban	81.2%	81.2%	0.00%	0.73%	1.16%	4.45%
	Rural	18.8%	18.8%	0.01%	0.73%	1.16%	4.45%
Marital status	Married	61.7%	61.7%	0.03%	3.30%	4.28%	7.83%
	Widowed	2.5%	2.5%	-0.06%	-5.46%	-4.51%	-1.71%
	Divorced	11.0%	11.0%	-0.02%	-2.67%	-0.92%	1.54%
	Separated	1.4%	1.4%	0.00%	-2.84%	-0.92%	2.89%
	Never married	23.4%	23.4%	-0.09%	4.13%	3.86%	8.23%
Highest degree	Bachelor/Professional	70.8%	70.9%	0.00%	29.56%	29.45%	54.31%
	Master's	26.4%	26.4%	0.00%	29.46%	30.14%	46.07%
	Doctorate	2.8%	2.8%	0.00%	52.59%	46.89%	129.90%
Disabled	Yes	5.1%	5.1%	0.00%	27.73%	30.85%	39.43%
	No	94.9%	94.9%	0.00%	27.73%	30.85%	39.43%
Hispanic	Yes	7.4%	7.4%	0.00%	15.85%	19.41%	52.03%
	No	92.6%	92.6%	0.00%	15.85%	19.41%	52.03%
Race	White	79.6%	79.6%	0.00%	-2.32%	1.55%	6.80%
	Black	8.9%	8.9%	0.00%	6.25%	10.82%	16.69%
	Asian	8.7%	8.7%	0.00%	6.13%	7.64%	19.69%
	AIAN	0.9%	0.9%	0.12%	33.28%	36.71%	63.89%
	NHPI	0.1%	0.1%	-0.67%	153.38%	162.35%	235.00%
	Other	1.7%	1.7%	-0.12%	-1.93%	1.53%	5.94%
U.S. citizen at birth	Yes	85.3%	85.3%	0.00%	4.54%	6.54%	12.24%
	No	14.7%	14.7%	-0.03%	4.54%	6.54%	12.24%
S&E Degree	Yes	41.3%	41.3%	0.00%	-8.68%	-9.37%	-2.88%
	No	58.7%	58.7%	0.00%	-8.68%	-9.37%	-2.88%
Gender	Male	-	-	-	-	-	-
	Female	100.0%	100.0%	0.00%	-	-	-
Age group	0-39	39.3%	39.3%	-0.02%	8.80%	13.58%	25.57%
	40+	60.7%	60.7%	0.01%	8.80%	13.58%	25.57%
Occupation	Comp/Math	2.1%	2.1%	0.00%	1.27%	1.58%	4.32%
	Life Sciences	0.4%	0.4%	0.00%	0.68%	1.04%	-0.58%
	Physical Sciences	0.5%	0.5%	0.00%	4.23%	5.03%	5.75%
	Social Sciences	0.8%	0.8%	0.00%	0.90%	0.73%	2.12%
	Engineering	0.7%	0.7%	0.00%	6.13%	3.48%	8.40%
	S&E-R Health	11.6%	11.6%	0.00%	4.44%	5.53%	17.74%
	S&E-R Non-Health	5.9%	5.9%	0.00%	23.25%	23.91%	29.86%
	Teachers	4.4%	4.4%	0.00%	2.62%	3.90%	5.79%
	Non S&E	61.4%	61.4%	0.00%	12.83%	18.15%	19.65%
	Not Working	12.1%	12.1%	0.00%	28.74%	43.82%	46.70%
		Average Relative Bias:		-0.02%	12.14%	14.18%	25.34%

AIAN - American Indian/Alaskan Native
NHPI - Native Hawaiian/Pacific Islander
S&E - Science and Engineering