Incorporating Variance and Geographic Specificity into the Imputation Frame Used in Weighting the American Community Survey Group Quarters Sample.

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Abstract

The American Community Survey, Group Quarters (GQ) imputation frame is the source of information about each GQ eligible for imputation, including the population. Each year, the population is updated in sampled GQs. However, the population is uncertain for GQs that are not sampled. Currently, this population is estimated with updates from sampled GQs. The populations are updated using a national level adjustment that does not account for the sampling variance. The purpose of this research is to look at updating GQ populations at lower levels of geography and incorporating the sampling variance into the frame. The updates are calculated at the state level and collapsed to higher levels of geography to meet sample size and extreme adjustment criteria. Variance is incorporated into this adjustment through the use of replicate weights, which enable variance to be easily incorporated within the GQ estimation procedure. By including both a collapsing algorithm and variance in the imputation frame, the variance of the GQ estimates are improved.

Key Words: Group Quarters, American Community Survey, Estimation, Variance Estimation, Weighting

1. Introduction

Currently, the American Community Survey (ACS) performs whole person imputation into GQs without interviews. Each year, GQs that are eligible for imputation are selected from a GQ imputation frame. Because of this, it is important that our frame contain the best and most up to date populations for all GQs.

The GQ imputation frame has GQs that are sampled, and GQs that are not sampled. GQs that are interviewed have updated population counts from data collection. However, GQs that are not sampled or are non-interviews do not have updated population counts.

For GQs that are not sampled, the expected population counts could differ from the actual population counts. If the expected population counts are not updated, then there could be imbalance in the imputation procedure. To update these population counts, a national level adjustment factor is applied to the GQs' expected population counts.

The purpose of this research is to localize population updates on the frame, to inform the imputation procedure. Calculating the adjustment factor at the subnational level facilitates localization. In addition, this research accounts for sampling variance in the imputation frame. This is because the frame counts are estimates. The variance is incorporated into the frame through a replicate weighting methodology. Disclaimer: Any views expressed are those of the authors and not necessarily those of the U.S. Census Bureau. The DRB approval number is CBDRB-FY19-ACSO002-B0018.

2. Background

2.1 Group Quarters

A group quarters is a place where people live or stay, in a group living arrangement. These living arrangements are atypical, and not similar to housing units (HU). GQs are classified into characteristic groups called GQ type groups. Examples include: Prisons, Nursing Homes, and College Dormitories. Owing to their different natures, GQs and HUs are separate survey operations that include GQ sampling and weighting.

For GQ sampling, the design area is the state level and each state has its own independent sampling rate. GQ sampling is systematic throughout the sampling process. Moreover, GQs are assigned a sampling size stratum based on their expected population size. Afterwards, GQ persons are sampled based upon the size of the GQ where they live.

Small GQs have 15 or less people. They are sampled as a whole. Large GQs have more than 15 people. They are sampled in multiples of 10 people, proportional to the size of the GQ, and at the state sampling rate.

The sampling methodology informs the estimation methodology. Large GQs tend to be in sample more often than small GQs. In fact, some GQs are in sample every year. This leads to small GQs, large GQs, and GQ sampled with certainty comprising the estimation size strata.

2.2 Direct Methodology

For data year 2010 and before, GQ estimates were obtained via direct estimation. The GQs were primarily weighted at the state area. Sampling baseweights were calculated as the inverse of the state sampling rate. A subsampling and observed population adjustment was applied to correct these baseweights. The adjustment was based on the size of the GQ. These weights were trimmed and excess weight was rationally distributed to other GQ persons in the same state by GQ type group. Afterwards, GQ interview weights were adjusted to account for non-respondent weights. The cells to produce the adjustment factor were regulated to produce reliable adjustments. This involved collapsing cells with too few interviews, or extreme adjustment factors. Finally, the person weights were controlled to independent population estimates at the state by GQ type group level. This adjustment also included regulations similar to the above (U.S. Census Bureau, 2010a).

The direct method produced characteristic estimates that were unreliable for substate areas. Specifically, clustering of the GQ sample led to an uneven substate coverage. This produced substate areas with little or no sample; where some estimates were calculated from information gathered in separate geographies.

2.3 Introduction of Imputation Methodology

For data year 2011, the GQ estimation methodology was updated to incorporate a whole person imputation process. Now GQ person records are imputed into GQs from interviewed records. This resulted in an increased coverage at substate levels, as well as reduced variances.

First, a GQ imputation frame is created. The sampling frame is updated with information gathered from the data collection. This includes GQ type, the current population of the

GQ, and whether the GQ should be deleted from the frame. Note that GQ type is a similar, yet more detailed version of GQ type group.

To select an accurate number of whole person imputations, the population estimates on the frame need to be updated. Specifically, the expected population of GQs that are not sampled are updated. Information from sampled GQs is used to update the expected population of GQs that are not sampled. This information is the relationship between the expected population at the time of sampling and the observed population at the time of data collection. The Not-in-sample Adjustment Factor (NAF) is used to perform this update. The factor attempts to estimate population trends within each GQ type group and GQ size stratum of the sample, at the national level. These trends are applied to GQs of the same GQ type group and GQ size stratum that are not sampled, with each GQ across the country receiving the same adjustment factor (U.S. Census Bureau, 2014a).

Finally, the frame includes a variable to identity GQs that are predominately of one sex. If a GQ has 90% of either sex then the GQ is assigned a label in accordance with that sex. It not then it is given a value of both. This facilitates an accurate representation of GQ persons in the imputation process. As GQs that are of one sex will have donors of that sex.

After the frame creation, GQs without interviews are selected for imputation, and interviewed persons are selected as donors to these GQs. The goal is to impute into enough GQs to cover each county by GQ type group on the frame. In addition, for the 5-year data, the ACS imputes into enough GQs to cover each tract by GQ type group on the frame. First, all of the large GQs without any interviews are selected for imputation. Second, small GQs without any interviews are selected for imputation to attain proper coverage.

The number of imputations selected reflects the sampling procedure. GQ persons are imputed based upon the size of the GQ where they live. Specifically, there are two imputation size strata. These are the large GQs and the small GQs. Large GQs have 2.5% of their expected population selected for imputation. Small GQs have 20% of their expected population selected for imputation. For both, if the number of imputations is less than one, then one imputation is selected.

Donors are selected to match the local geography, and GQ type characteristics of the GQ set for imputation. An ample amount of donors must be present, or else an algorithm must search for donors that are in a higher level geography, and are somewhat different in GQ type. The search for donors begins in the same county and GQ type of the GQ set for imputation. If there are not enough donors then the search is expanded. First, donors are sought in the same county, but with a slightly different GQ type. If a donor is still not found, then a search for one is performed in the same state within the same GQ type. This process continues up to the national level, until a donor is found. In addition, the ACS prevents the overuse of the same donor at the tract and county level. Overused donors are swapped with other, similar donors.

Baseweights are computed for imputations and interviews. Large GQs represent themselves. For a large GQ, each imputation or interview is given an equal baseweight across the GQ. These baseweights sum to the GQ's expected population. Small GQs represent the tract by GQ type group where they are located. For a small GQ, each imputation or interview is given a baseweight across the small GQs located in the same tract and GQ type group.

The imputation frame is used to determine the substate distribution of GQ persons for constraint adjustments. Specifically, there are constraint adjustments applied at the tract level, the county level, and the state level.

Finally, the weighted population is controlled to an independent estimate at the state by GQ type group level. Afterwards, the weighted persons are rounded to create final weighted persons.

2.4 Variance Estimation

The ACS uses a replicate weighting methodology to estimate the variance through the successive differences replication method (SDR). Specifically, the ACS creates sets of 80 replicate factors for different classes of GQs. Replicate factors are multiplied by GQ person baseweights to produce replicate weights. Weighting adjustments are applied to both the production weight and the replicate weights. Finally, variance estimates are calculated from the production weight and the replicate weights. In essence, SDR is a measurement of the variability between the production weight and the replicate weights (U.S. Census Bureau, 2014b).

For the Direct method, replicate factors were assigned directly to the GQ person baseweights to produce replicate baseweights (U.S. Census Bureau, 2010b). When the current production method was created, frame constraints were applied to the baseweights and the replicate baseweights. In addition, design factors were applied to the replicate weights..

Design factors are applied to inflate the variance estimates. The reason the variance estimates need to be inflated is due to imputation. The design factors are computed for each state by GQ type group (Asiala and Castro, 2013).

When applying constraints, some tracts had no variance in their population estimates. In essence, the frame constraints were assumed to be constant.. The ACS treated the imputation frame as the "truth" rather than account for the sampling variance from the imputation frame. This reason coupled with a lack of GQs at the tract level produced no population variance for some tracts. To impart population variance to all tracts, the ACS applied replicate weights after the implementation of tract level constraints.

3. Research Questions

- *What are the collapsing patterns for algorithms that calculate the NAF at the subnational level?*
- *How does the collapsing algorithm effect coverage rates?*
- *How does the collapsing algorithm and frame replicate weights effect CVs?*
- *How does the collapsing algorithm effect characteristic final weighted estimates?*
- *How does the collapsing algorithm and frame replicate weights effect characteristic CVs?*

4. Methodology

4.1 Collapsing Algorithms

The researchers have developed a collapsing algorithm to estimate the NAF at localized levels of geography. This will produce localized, population updates to the frame. This in turn will localize the final population estimates.

The collapsing algorithm has two parameters to regulate the amount of cell collapsing. The threshold parameter keeps the NAF between an upper bound and a lower bound. The lower bound is the reciprocal of the upper bound. If a NAF is outside of the bounds then cell collapsing will occur to a higher geography. The two upper bounds tested are 3.5 and 2.

NSREC is the other parameter. NSREC keeps the number of sampled GQs above a threshold. If the number of sampled GQs is below NSREC then cell collapsing will occur to a higher geography. The three NSREC values tested are 5, 10, and 15.

Collapsing cells are defined by GQ type group, GQ size stratum, and geography level. Collapsing only occurs across geography. GQ type groups and GQ size strata are never collapsed. The collapsing algorithm begins with all frame GQs placed into their starting cells. These cells have GQs with the same GQ type group, GQ size stratum, and state geography. The algorithm computes the NAF for each cell. If one of the parameter conditions fails then all cells within the same division geography collapse into one cell. The algorithm continues checking collapsed cells at division geography, and then region geography. If collapsed cells at the region geography fail to meet our two conditions, then all of the frame GQs of the same GQ type group and GQ size stratum collapse into one cell. On the other hand, if all cells within a geography level meet our two conditions then the cells do not collapse.

NAFs are computed from these collapsed cells. For example, if a group of cells collapses to the division geography then a NAF is computed at the division geography. This NAF is then applied to all GQ population updates within that collapsed cell.

The researchers evaluated different combinations of the two constraints to find an optimal solution. These constraints include:

- Assigning NAF at the state geography (No Collapsing).
- A NAF threshold of 3.5, and 5 sampled GQs in a cell (CLPSE 3.5 / 5).
- A NAF threshold of 3.5, and 10 sampled GQs in a cell (CLPSE 3.5 / 10).
- A NAF threshold of 3.5, and 15 sampled GQs in a cell (CLPSE 3.5 / 15).
- A NAF threshold of 2, and 5 sampled GQs in a cell (CLPSE 2 / 5).
- A NAF threshold of 2, and 10 sampled GQs in a cell (CLPSE 2 / 10).
- A NAF threshold of 2, and 15 sampled GQs in a cell (CLPSE 2 / 15).
- Assigning NAF at the national level (Complete Collapsing)

Note that Complete Collapsing is the current method used in production.

4.2 Variance on the GQ Imputation Frame

The researchers seek to account for the variance on the frame. The frame counts are used in the imputation, and in the calibration of estimates. GQs that are not sampled have estimated frame counts. The estimated counts are a function of the sample. This leads to sampling variation on the frame counts. To account for the sampling variation, the researchers have generated replicate weights on the frame. Variances from the replicate weights are calculated using a successive differences replication method (Fay and Train, 1995). The variance estimation formula is presented below, where θ_0 is the production estimate and the θ_i are the replicate estimates.

$$VAR(\hat{\theta}) = \frac{4}{80}\sum_{i=1}^{80}(\theta_i - \theta_0)^2$$

In our current production methodology, the replicate factors are applied not to the baseweights as would be expected but rather to the tract constraint weights. This is due to the fact that currently there is no variance incorporated into the frame counts. So when the frame constraints are applied at the tract level they effectively function to directly control the weights' totals and remove all the variance. Now that there is variance incorporated into these constraints, the GQ weighting can return to a more typical application of the replicate factors to the baseweights. This will give every tract by GQ type group on the frame a population estimate with a non-zero variance.

Because the frame constraints impose their variance structure on the pre-controlled estimates they produce similar variance estimates. Therefore, the research is focused on the pre-controlled variance estimates rather than the frame variance estimates. The researchers seek to compare the variance estimates from their current production method and methods that use a direct method. Whereby direct method, it is meant a method that applies replicate factors directly to the GQ person baseweights to create replicate person weights.

4.3 Measurements of Research Effectiveness

The amount of the collapsing was evaluated by counting the number of cells that collapsed to each level of geography. The cells were counted at the national level and at the GQ type group level. The distribution of counts were comparedamong collapsing algorithms to obtain an understanding of how their parameters affect their collapsing patterns.

The researchers measured each collapsing method's ability to obtain optimal coverage by counting the number of state by GQ type groups with a coverage rate between 70% and 125%.

In addition, coverage rates were used to compare pre-controlled estimates among the direct method, the production method, and the collapsing methods. These comparisons are for estimates summarized at the national level, GQ type group level, state level, and state by GQ type group level. Results with few cells have all entries tabulated for comparison. These include the national level and GQ type group level comparisons. However, state level and state by GQ type group level comparisons have percentiles tables and other descriptive statistics such the mean, median, and standard deviation. This distributional method of comparison is necessary due to the immense amount of results.

Furthermore, a similar comparison was made for the pre-controlled variances of these methods using their pre-controlled CVs.

For substate distributions, the researchers evaluated pre-controlled variance and final variance with CVs. Specifically, all the methods' CVs were compared at the county geography. Because of the large amount of results, percentile tables and other descriptive statistics were tabulated for comparison. The other descriptive statistics include the mean, median, and standard deviation.

Finally, the researchers compared all the methods' characteristic final estimates and the characteristic final variances. The characteristic final variances were compared using CVs. These characteristics included Sex, Age Group, Hispanic Origin, Race, Employment Status, Educational Attainment, and Poverty Status. All of these results are tabulated as separate entries.

5. Limitations

The research is for the 1-year estimates. No research has been done for the 5-year estimates yet. However, 1-year weighting and 5-year weighting use the same methodology. Thus, it is expected that the collapsing algorithms and frame variance have similar impacts to the 5-year estimates. Additionally, the frame is a 1-year construct. It is sensible to look at the 1-year weighting before the 5-year weighting. However, the plan is to evaluate the collapsing algorithms and frame variance for the 5-year weighting in the future.

The GQ size strata on the GQ sampling frame are different compared to the GQ size strata on the GQ imputation frame. There are two GQ size strata for sampling. These are small and large GQ strata (U.S. Census Bureau, 2014c). However, there are three GQ size strata for the weighting. The actual problem with having different size strata is for frame variance. GQs sampled with certainty are assumed to represent themselves in the estimation. However, these GQs are sampled with other large GQs that may not be selected for interview. Hence, GQs sampled with certainty actually represent themselves and other large GQs that are not selected. This should cause an increase in the variance of the estimates. The researchers correct for this by applying replicate factors to the GQs sampled with certainty.

For the computation of the NAF, the collapsing is across geography. Collapsing is not across GQ type group or GQ size stratum. The algorithm collapses cells with similar geography because nearby geographical areas should have similar population changes and population characteristics. On the other hand, GQ type groups are defined because their populations are inherently different from one another. A population change in one GQ type group should not be positively correlated with the population change in another GQ type group. For example, an increase in the population of Nursing Homes should not be related to the population change in College Dormitories. In addition, by not combining these GQ type group cells their inherent population structure remains intact. Finally, the algorithm does not collapse across GQ size stratum for two reasons. First, the sampling of GQs is defined by GQ size strata. The information received from small GQs is not directly comparable to the information received from large GQs. Not collapsing across size stratum preserves the information from the each stratum. Second, GQs sampled with certainty always have updated information. While small GQs and large GQs that are not sampled with certainty do not have the most recent information. It would be incorrect to assume that the population changes from GQs sampled with certainty could be applied to smaller GQs. The information gathered has a different structure and should not be applied as a collapsed cell.

For the NAF, the algorithm computes within GQ type group rather than GQ type. On the frame, the number of GQs in each GQ type can be sparse. This sparsity would lead to small cells sizes for the NAF computation. The cells would most likely completely collapse to the national level. This complete collapsing would defeat the objective to geographically localize the NAF. However, there is one exception. Correctional Facilities are split into two GQ type groups. These are Federal Prisons and Other Correctional Facilities. This is because there is more recent information for Federal Prisons, and there are many Federal Prisons on the frame.

6. Results

Note some tables are presented at the end of the paper.

6.1 What are the collapsing patterns for algorithms that calculate the NAF at the subnational level?

6.1.1 In general (Table 1.1)
As expected, increasing the NAF threshold decreases the amount of collapsing. On the other hand, decreasing NSREC decreases the amount of collapsing. Decreasing the amount of collapsing produces more localized estimates. The change in collapsing is especially noticeable in the CLPSE 3.5 / 5 method. The number of cells collapsing to the national level has decreased dramatically from an interplay between the increase in NAF threshold and a decrease in NSREC. The cells will be spread among the lower geographic levels. This will lead to more localized population updates for more GQs on the frame.

The parametrized algorithms prove successful in the redistribution of estimation cells. They redistribute many cells between state geography and national geography. However, most of the cells collapse to the national level. Collapsing to the national level is like the Complete Collapsing method, where all cells collapse to the national level. Furthermore, our current production method (Production method) collapses all cells to the national level.

Table 1.1: Number of Cells Calculated at Each Level of Geography by Collapsing
Data Source: 2016, 1-year, ACS data

Estimation Methodology	National	Region	Division	State
No Collapsing	0	0	0	965
CLPSE 3.5 / 5	326	145	283	211
CLPSE 3.5 / 10	415	148	281	121
CLPSE 3.5 / 15	415	214	239	97
CLPSE 2 / 5	427	103	256	179
CLPSE 2 / 10	466	134	252	113
CLPSE 2 / 15	466	192	210	97
Complete Collapsing	965	0	0	0

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6.1.2 By GQ type group (Tables A.1 through A.7)
Fixing NSREC equal to 10, and varying the NAF threshold, the collapsing patterns are evaluated across GQ type groups. Increasing the threshold usually corresponds to less collapsing. This is especially pronounced in College Dormitories. When the NAF threshold increases then the number cells collapsing to the national level are cut in half. These cells are spread among the other geographic levels. This leads to more College Dormitories having localized population updates. On the other hand, Other Long-Term

Care Facilities, and Other Non-Institutional Facilities have the same collapsing pattern across threshold values. If the same GQs are in the same geographic cells, then both parametrized algorithms will produce the same population updates for these GQ type groups.

For all GQ type groups, the parametrized algorithms successfully redistribute estimation cells between state and national geography. Some of the GQ type groups do not have any cells collapsing to the state geography. These GQ type groups are Juvenile Detention Facilities, Other Long-Term Care Facilities, and Military Facilities. There are less of these GQs compared to other GQ type groups. In addition, these GQs are sparsely spread across the country. For these reasons, the number of sampled GQs can be small in a collapsing cell. If the number of sampled GQs is too small then the cell is collapsed to a higher geography. On a different note, most of the GQ type groups have a large proportion of their cells collapsing to the national geography. However, Juvenile Facilities and Other Non-Institutional Facilities have a small proportion of their cells collapsing to the national geography. For these GQ type groups, the collapsing pattern is about the same for both NAF threshold parameter values of 2 or 3.5.

6.2 How does the collapsing algorithm effect coverage rates?

6.2.1 Coverage Rates close to 100% (Table 2.1)

The collapsing algorithms have similar coverage that is close to 100%. Specifically, the algorithms have about the same number of state by GQ type group cells with coverage rates between 70% and 125%. However, more collapsing produces more cells that have a coverage rate between 70% and 125%. For instance, No Collapsing produces the least number of these cells. Complete Collapsing produces the most number of these cells. And the parametrized algorithms are in between. The lack of collapsing produces estimates with higher variance. These cells may account for the reason there are less cells with a coverage rate between 70% and 125%.

Table 2.1: Number of state by GQ type group cells (out of 364) that have a coverage rate between 70% and 125%.
Data Source: 2016, 1-year, ACS data

Estimation Methodology	Number of Cells
No Collapsing	216
CLPSE 3.5 / 5	228
CLPSE 3.5 / 10	229
CLPSE 3.5 / 15	224
CLPSE 2 / 5	228
CLPSE 2 / 10	228
CLPSE 2 / 15	227
Complete Collapsing	241

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6.2.2 National summarization of Coverage Rates (Table 2.2)

The coverage rates summarized at the national geography are similar. The Direct method has the highest coverage rate. The CLPSE 2 / 5 method has the lowest coverage rate. However, these two coverage rates differ by less than 2%.

Table 2.2: National level, coverage rates.
Data Source: 2016, 1-year, ACS data

Estimation Methodology	Coverage Rates
Direct	90.89%
Production	89.44%
No Collapsing	89.68%
CLPSE 3.5 / 5	89.45%
CLPSE 3.5 / 10	89.45%
CLPSE 3.5 / 15	89.44%
CLPSE 2 / 5	89.41%
CLPSE 2 / 10	89.43%
CLPSE 2 / 15	89.42%
Complete Collapsing	89.44%

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6.2.3 GQ type group summarization of Coverage Rates (Table B.1)
Within GQ type group, coverage rates are similar among the different estimation methods. However, the No Collapsing method is sometimes, distinctly different from all other methods. Specifically, the No Collapsing method is extremely different for Other Long-Term Care Facilities. In addition, it is slightly different compared to the other collapsing methods for most other GQ type groups. The extreme difference for Other Long-Term Care Facilities is probably due to the high diversity of people in the GQs, the sparsity of these GQs, and the sparsity of the GQ people. With no collapsing, there may be extreme NAF estimates from only a few of these GQs. This makes extreme population updates; and this leads to an extreme coverage rate.

6.2.4 State summarization of Coverage Rates (Table 2.3 and Table 2.4)
These tables describe the state level distribution of coverage rates for all estimation methodologies. For example, the minimum coverage rate represents the state with the lowest coverage rate. The estimation methodologies have similar coverage rate distributions except in the tails. The differences are extremely pronounced for the maximum coverage rates. For example, the Direct method produces a maximum coverage rate of 128.0%. This is nearly 20% higher than most other methods' maximum coverage rates. Furthermore, these extreme values probably cause the differences in standard deviation among the coverage rate distributions. These extreme values do not have a strong effect on the similarity of the mean and median coverage rates. Even though the Direct method has the highest median and mean coverage rate, all the methods are similar in these statistics.

Table 2.3: State level, coverage rate percentiles.
Data Source: 2016, 1-year, ACS data

Estimation Methodology	Coverage Rate percentiles				
	Min	P25	P50	P75	Max
Direct	72.85%	84.98%	90.96%	95.99%	128.0%
Production	73.83%	85.71%	90.17%	94.35%	106.2%
No Collapsing	74.09%	83.84%	89.95%	97.58%	112.6%
CLPSE 3.5 / 5	67.79%	84.60%	90.45%	96.47%	107.7%
CLPSE 3.5 / 10	71.28%	85.43%	89.89%	96.35%	111.0%
CLPSE 3.5 / 15	72.15%	85.73%	88.88%	95.08%	107.6%
CLPSE 2 / 5	68.18%	86.80%	89.92%	95.21%	106.5%
CLPSE 2 / 10	71.81%	86.62%	88.98%	95.37%	108.6%
CLPSE 2 / 15	72.68%	86.29%	88.98%	94.85%	108.5%
Complete Collapsing	73.83%	85.71%	90.17%	94.35%	106.2%

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Table 2.4: State level, coverage rate, descriptive statistics.
Data Source: 2016, 1-year, ACS data

Estimation Methodology	Coverage Rate statistics		
	Standard Deviation	Mean	Median
Direct	10.77%	91.72%	90.96%
Production	7.15%	90.27%	90.17%
No Collapsing	9.71%	91.18%	89.95%
CLPSE 3.5 / 5	8.35%	90.43%	90.45%
CLPSE 3.5 / 10	8.06%	90.38%	89.89%
CLPSE 3.5 / 15	7.62%	90.22%	88.88%
CLPSE 2 / 5	7.64%	90.30%	89.92%
CLPSE 2 / 10	7.58%	90.36%	88.98%
CLPSE 2 / 15	7.61%	90.30%	88.98%
Complete Collapsing	7.15%	90.27%	90.17%

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6.2.5 State by GQ type group summarization of Coverage Rates (Table 2.5 and Table 2.6)
These tables describe the state by GQ type group level distribution of coverage rates for all estimation methodologies. The estimation methodologies have similar coverage rate distributions except in the right tail. The differences are extremely large for the maximum coverage rate. For example, the parametrized collapsing methods have a maximum coverage rate of 7,325%, while the Direct method has a maximum coverage rate of about 765%. These trends are reflected in the standard deviation, mean, and median of the coverage rates. The standard deviation and mean are positively correlated with the maximum. On the other hand, the median is associated with the bulk of the distribution of coverage rates. That is the median coverage rates are similar between the different estimation methodologies. Moreover, the parametrized collapsing algorithms produce slightly higher median coverage rates compared to the other estimation methods.

Table 2.5: State by GQ type group level, coverage rate percentiles.
Data Source: 2016, 1-year, ACS data

Estimation Methodology	Coverage Rate percentiles				
	Min	**P25**	**P50**	**P75**	**Max**
Direct	3.08%	64.59%	85.10%	101.5%	764.9%
Production	1.59%	68.89%	84.90%	97.37%	4,146%
No Collapsing	0.44%	62.63%	85.54%	99.32%	1,115%
CLPSE 3.5 / 5	1.59%	65.43%	86.36%	99.23%	7,325%
CLPSE 3.5 / 10	1.59%	65.73%	87.32%	98.08%	7,325%
CLPSE 3.5 / 15	1.59%	64.90%	87.22%	98.08%	7,325%
CLPSE 2 / 5	1.59%	65.73%	86.56%	99.32%	7,325%
CLPSE 2 / 10	1.59%	65.80%	87.40%	98.64%	7,325%
CLPSE 2 / 15	1.59%	65.43%	86.98%	97.84%	7,325%
Complete Collapsing	1.59%	68.89%	84.90%	97.37%	4,146%

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Table 2.6: State by GQ type group level, coverage rate, descriptive statistics.
Data Source: 2016, 1-year, ACS data

Estimation Methodology	Coverage Rate statistics		
	Standard Deviation	**Mean**	**Median**
Direct	65.53%	88.84%	85.10%
Production	215.8%	96.62%	84.90%
No Collapsing	71.77%	88.77%	85.54%
CLPSE 3.5 / 5	382.4%	107.3%	86.36%
CLPSE 3.5 / 10	382.2%	106.4%	87.32%
CLPSE 3.5 / 15	382.1%	105.3%	87.22%
CLPSE 2 / 5	382.1%	106.1%	86.56%
CLPSE 2 / 10	382.0%	106.2%	87.40%
CLPSE 2 / 15	382.0%	105.7%	86.98%
Complete Collapsing	215.8%	96.62%	84.90%

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6.3 How does the collapsing algorithm and frame replicate weights effect CVs?

6.3.1 National summarization of pre-controlled CVs (Table 3.1)

All the pre-controlled CVs are less than 1.00%. This makes it difficult to declare any meaningful results. However, the collapsing algorithms have the largest CVs. They are all around 1.00%. Out of the collapsing algorithms, the No Collapsing method has the largest CV. Yet, the Complete Collapsing method does not have the lowest CV. This was the expectation due to all the population updates being generalized to the national level. The aggregation is at the national geography, and this may have resulted in the lack of intended localization effects. On a different note, the Production method has the smallest CV of 0.42%. Differences between the Production method and the collapsing algorithms are expected. The collapsing algorithms have replicate weights applied to the GQs on the frame. The Production method does not.

Table 3.1: National level, pre-controlled CVs.
Data Source: 2016, 1-year, ACS data

Estimation Methodology	CVs
Direct	0.68%
Production	0.42%
No Collapsing	0.99%
CLPSE 3.5 / 5	0.96%
CLPSE 3.5 / 10	0.97%
CLPSE 3.5 / 15	0.97%
CLPSE 2 / 5	0.95%
CLPSE 2 / 10	0.95%
CLPSE 2 / 15	0.95%
Complete Collapsing	0.97%

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6.3.2 GQ type group summarization of pre-controlled CVs (Table C.1)

Most of the CVs are less than 10%. However, Other Long-Term Care Facilities have CVs closer to 12%. Within GQ type group, the CVs are usually similar. Yet, there are some notable differences among the methods. For instance, Other Long-Term Care Facilities have a low CV for the No Collapsing method. This is negatively correlated with the extreme coverage rate produced. Hence, it makes sense that the much larger population estimate produces a much smaller CV. On a different note, across the GQ type groups there is no certain relationship among the parametrized algorithms' CVs. GQ type group is a general aggregation and is not an active part of the collapsing algorithms. The localization effects may be nullified by these factors.

6.3.3 State summarization of pre-controlled CVs (Table 3.2 and Table 3.3)

It is expected that accounting for the variance from the NAF will increase variance above the Production method. In addition, more information gained from the imputations should decrease the variance below the Direct method. In general, this is what happened. For the median CVs, the parametrized methods have larger variance compared to the Production method, and smaller variance compared to the Direct method. Moreover, there are some large differences among the methods towards the right tail. The maximum Direct method CV is 23.10%, while the maximum Complete Collapsing method CV is 3.28%. On a different note, there is a pattern within the parametrized algorithms. There is an increase in the median CVs as the NAF threshold increases. Additionally, there is an increase in the median CVs as NSREC decreases. These results are expected as less regulations on the NAF cells should produce more localized estimates and higher variances.

Table 3.2: State level, pre-controlled, CV percentiles.
Data Source: 2016, 1-year, ACS data

Estimation Methodology	CV percentiles				
	Min	P25	P50	P75	Max
Direct	1.90%	3.45%	4.64%	5.96%	23.10%
Production	1.04%	2.31%	2.98%	4.22%	8.87%
No Collapsing	1.72%	3.79%	4.67%	7.10%	20.64%
CLPSE 3.5 / 5	1.93%	3.01%	4.18%	5.32%	15.94%
CLPSE 3.5 / 10	1.69%	2.76%	3.57%	4.44%	15.64%
CLPSE 3.5 / 15	1.67%	2.55%	3.35%	4.17%	7.47%
CLPSE 2 / 5	1.91%	2.66%	3.88%	4.62%	14.14%
CLPSE 2 / 10	1.67%	2.53%	3.36%	4.25%	13.59%
CLPSE 2 / 15	1.67%	2.36%	3.08%	4.07%	7.51%
Complete Collapsing	0.59%	0.96%	1.10%	1.23%	3.28%

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Table 3.3: State level, pre-controlled, CV descriptive statistics.
Data Source: 2016, 1-year, ACS data

Estimation Methodology	CV statistics		
	Standard Deviation	Mean	Median
Direct	3.66%	5.56%	4.64%
Production	1.55%	3.36%	2.98%
No Collapsing	4.11%	6.15%	4.67%
CLPSE 3.5 / 5	2.60%	4.66%	4.18%
CLPSE 3.5 / 10	2.52%	4.20%	3.57%
CLPSE 3.5 / 15	1.20%	3.45%	3.35%
CLPSE 2 / 5	1.95%	4.04%	3.88%
CLPSE 2 / 10	1.88%	3.68%	3.36%
CLPSE 2 / 15	1.21%	3.34%	3.08%
Complete Collapsing	0.45%	1.19%	1.10%

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6.3.4 State by GQ type group summarization of pre-controlled CVs (Table 3.4 and Table 3.5)

Similarly to the state pre-controlled CVs, most of the parametrized methods have larger median CVs compared to the Production method, and smaller median CVs compared to the Direct method. Specifically, the Direct method has higher CVs throughout the distribution compared to all other estimation methods. For example, the 75th percentile is 41.09%. The next highest estimation method has a 75th percentile of 26.20%. This is probably due to the lack of imputation records in the Direct method. The No Collapsing method and the CLPSE 3.5 / 5 method have the next highest median and mean CVs. This is expected, as more localized updates should produce greater variance in the estimates. The No Collapsing method provides population updates at the state geography. The CLPSE 3.5 / 5 method collapses the least, and provides the most localized methods among the parametrized algorithms. On a different note, the Complete Collapsing method has the lowest CVs throughout its distribution. The mean and median agree with this finding. The Complete Collapsing method has the most generalized population updates. These generalized updates should produce lower variances in the estimates. Moreover, the Production method and the rest of the parametrized algorithms have similar CV distributions. This is reflected in the medians of these distributions. Finally, the parametrized algorithms produce the expected relationship between the parameters and the CVs. When the NAF threshold increases there is an increase in the median CVs. When NSREC decreases there is an increase in the median CVs.

Table 3.4: State by GQ type group level, pre-controlled, CV percentiles.
Data Source: 2016, 1-year, ACS data

Estimation Methodology	CV percentiles				
	Min	P25	P50	P75	Max
Direct	1.26%	7.22%	16.69%	41.09%	100.9%
Production	1.86%	5.30%	9.29%	17.83%	120.0%
No Collapsing	0.00%	4.91%	11.07%	26.20%	200.0%
CLPSE 3.5 / 5	0.48%	6.44%	11.66%	21.77%	86.60%
CLPSE 3.5 / 10	0.48%	4.95%	9.83%	17.78%	86.60%
CLPSE 3.5 / 15	0.48%	4.71%	9.47%	16.46%	86.60%
CLPSE 2 / 5	0.48%	5.91%	9.97%	19.53%	86.60%
CLPSE 2 / 10	0.48%	4.68%	9.42%	16.57%	86.60%
CLPSE 2 / 15	0.48%	4.44%	9.17%	14.75%	86.60%
Complete Collapsing	0.30%	1.61%	3.57%	8.35%	86.60%

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Table 3.5: State by GQ type group level, pre-controlled, CV descriptive statistics.
Data Source: 2016, 1-year, ACS data

Estimation Methodology	CV statistics		
	Standard Deviation	Mean	Median
Direct	30.31%	29.74%	16.69%
Production	17.95%	15.86%	9.29%
No Collapsing	30.46%	21.52%	11.07%
CLPSE 3.5 / 5	15.15%	16.28%	11.66%
CLPSE 3.5 / 10	14.84%	14.14%	9.83%
CLPSE 3.5 / 15	13.49%	13.13%	9.47%
CLPSE 2 / 5	13.77%	14.66%	9.97%
CLPSE 2 / 10	13.76%	13.35%	9.42%
CLPSE 2 / 15	13.45%	12.78%	9.17%
Complete Collapsing	10.87%	7.13%	3.57%

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6.3.5 County summarization of pre-controlled and final estimate CVs (Table 3.6, Table 3.7, Table D.1, and Table D.2)

For the county level pre-controlled CVs, the parametrized methods are below both the Production method and the Direct method, in median CVs. This is for two reasons. First, the imputations provide a density of data at the substate geography. Second, the parametrized methods are localized estimation methods. For these two reasons, the parametrized methods produce more precise estimates compared to the Production method and the Direct method. On a different note, the collapsing methods' pre-controlled CVs have the expected pattern. For example, the No Collapsing method has the highest median pre-controlled CV. The Complete Collapsing method has the lowest median pre-controlled CV. In essence, when the parameters are expected to produce more localized population updates then the CVs become larger.

For the county level final estimate CVs, the results are similar to the pre-controlled results. The parametrized methods are below both the Production method and the Direct method, in median CVs. However for the parametrized methods, the final estimate CVs are smaller than the pre-controlled CVs. The median CVs reflect this notion.

Table 3.6: County level, pre-controlled, CV descriptive statistics.
Data Source: 2016, 1-year, ACS data

Estimation Methodology	CV statistics		
	Standard Deviation	Mean	Median
Direct	33.07%	57.59%	51.57%
Production	33.14%	47.47%	39.33%
No Collapsing	13.53%	9.75%	6.30%
CLPSE 3.5 / 5	9.70%	8.59%	6.01%
CLPSE 3.5 / 10	8.37%	7.25%	5.25%
CLPSE 3.5 / 15	7.41%	6.68%	5.13%
CLPSE 2 / 5	7.78%	7.36%	5.71%
CLPSE 2 / 10	7.55%	6.73%	5.08%
CLPSE 2 / 15	7.20%	6.44%	4.95%
Complete Collapsing	6.74%	3.34%	1.81%

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Table 3.7: County level, final estimate, CV descriptive statistics.
Data Source: 2016, 1-year, ACS data

Estimation Methodology	CV statistics		
	Standard Deviation	Mean	Median
Direct	33.30%	57.68%	51.77%
Production	33.92%	47.26%	38.14%
No Collapsing	14.31%	7.49%	3.97%
CLPSE 3.5 / 5	10.62%	6.29%	3.54%
CLPSE 3.5 / 10	9.98%	5.40%	3.12%
CLPSE 3.5 / 15	9.76%	5.11%	3.05%
CLPSE 2 / 5	9.78%	5.34%	3.20%
CLPSE 2 / 10	9.71%	4.99%	2.90%
CLPSE 2 / 15	9.66%	4.88%	2.86%
Complete Collapsing	9.94%	3.50%	1.41%

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6.4 How does the collapsing algorithm effect characteristic final weighted estimates?

6.4.1 Sex summarization of final weighted estimates (Table E.1)

The Sex level, final weighted estimates are consistent among the estimation methods. However, the Direct method and Production method have the largest estimates among all the methods. On the other hand, the No Collapsing method has the smallest estimates. For example, the Production method has an estimate of 4,948,000 males in GQs, while the No Collapsing method has an estimate of 4,656,000 males in GQs. On a different note, the population estimates have a relationship with the collapsing parameters. The parameters that produce more collapsing produce higher population estimates.

6.4.2 Age Group summarization of final weighted estimates (Table E.2)

The Age Group level, final weighted estimates are consistent among the estimation methods. However, the No Collapsing method consistently has the smallest estimates among all the methods. On a different note, the population estimates have a relationship with the collapsing parameters. Often, the parameters that produced more collapsing produce higher population estimates. This is especially true for the NSREC parameter. However, there are some Age Groups that do not follow this pattern. Specifically, these Age Groups are “09 to 16” and “57 to 64”. Here some estimation methods with lower collapsing have produced higher population estimates. Still, within Age Group, the population estimates produced by the parametrized methods are similar to each other.

6.4.3 Hispanic Origin summarization of final weighted estimates (Table E.3)

The Hispanic Origin level, final weighted estimates are consistent among the estimation methods. However across Hispanic Origin, the Direct method and the Production method have the largest population estimates among all the methods. On the other hand, the No Collapsing method has the lowest population estimates. For example, the “Not Hispanic” population estimate for the Direct method is 7,027,000. The “Not Hispanic” population estimate for the No Collapsing method is 6,600,000. Finally, the population estimates have a relationship with the collapsing parameters. The parameters that produce more collapsing produce higher population estimates.

6.4.4 Race summarization of final weighted estimates (Table E.4)

The Race level, final weighted estimates are consistent among the estimation methods. However, often the No Collapsing method has the lowest population estimates among all the methods. On a different note, the population estimates usually have a consistent relationship with the collapsing parameters. The parameters that produce more collapsing produce higher population estimates. However for “Native Hawaiian and Other Pacific Islander”, this pattern does not exactly hold. Across NSREC the pattern holds. Yet, higher NAF thresholds produce larger population estimates. Higher NAF thresholds are associated with less collapsing. Still, the No Collapsing method produces a smaller population estimate than the Complete Collapsing method.

6.4.5 Employment Status summarization of final weighted estimates (Table E.5)

The Employment Status level, final weighted estimates are consistent among the estimation methods. Often the No Collapsing method has the lowest population estimates among all the methods. Finally, across Employment Status, there is no discernable relationship between the population estimates and the collapsing parameters.

6.4.6 Educational Attainment summarization of final weighted estimates (Table E.6)

The Educational Attainment level, final weighted estimates are consistent among the estimation methods. The Direct Method and the Production method have the largest population estimates among all the methods. On the other hand, the No Collapsing method has the smallest population estimates among all the methods. For example, the Production method has a “College degree attained” population estimate of 755,300. While, the No Collapsing method has a “College degree attained” population estimate of 701,000. Finally, the population estimates usually have a consistent relationship with the collapsing parameters. The parameters that produce more collapsing produce higher population estimates. This is especially true for the NSREC parameter. The higher the NSREC the higher the estimate.

6.4.7 Poverty Status summarization of final weighted estimates (Table E.7)

The Poverty Status level, final weighted estimates are consistent among the estimation methods. The Direct Method and the Production method have the largest population estimates among all the methods. On the other hand, the No Collapsing method has the smallest population estimates among all the methods. For example, the Production method estimates the number of GQ people in poverty as 759,200. The No Collapsing method estimates this number as 641,000. When the NAF threshold equals 3.5, then there is a relationship between NSREC and the population estimates. As NSREC increases the population estimates increase.

6.5 How does the collapsing algorithm and frame replicate weights effect characteristic CVs?

6.5.1 Sex summarization of final weighted CVs (Table F.1)

The Sex level, final weighted CVs are similar among the estimation methods. They are all less than 1.00%. However, the Direct method has the highest CVs among all the methods. The other methods have more similar CVs. For example, the Direct method has a female population CV of 0.63%. While the CLPSE 2 / 15 method has the lowest female population CV of 0.32%. On a different note, the CV estimates have a relationship with the collapsing parameters. Decreasing NSREC increases the CV. Moreover, the No Collapsing method has larger CVs than the Complete Collapsing method.

6.5.2 Age Group summarization of final weighted CVs (Table F.2)
The Age Group level, final weighted CVs are consistent among the estimation methods. Most of the CVs are below 2.00%. However, Age Group “08 or less” has much higher CVs. These CVs range from the Direct method’s 11.30% to the Complete Collapsing method’s 4.45%. Note that this Age Group has the smallest population estimates out of all the Age Groups. Specifically, these population estimates are about a fourth or a fifth of the next lowest Age Group population estimates. For example, the No Collapsing method has a “08 or less” population estimate of 19,090, and a “09 to 16” population estimate of 88,760. On a different note, often the Complete Collapsing method has the smallest CV within an Age Group. Finally, across Age Group there is no discernable relationship between the CVs and the collapsing parameters.

6.5.3 Hispanic Origin summarization of final weighted CVs (Table F.3)
The Hispanic Origin level, final weighted CVs are similar among the estimation methods. They are all less than 2.00%. Specifically, all the methods’ “Not Hispanic” CVs are close to each other. The largest CV is 0.19% and comes from the No Collapsing method. The smallest CV is 0.10% and comes from the Complete Collapsing method. On the other hand, the “Hispanic” CVs are spread out among all the methods. Specifically, the Direct method is larger than the other estimation methods. The Direct method’s CV is 1.15%. The other methods’ CVs have a range between 0.63% and 0.78%. Finally, across Hispanic Origin there is no discernable relationship between the CVs and the collapsing parameters. However, the No Collapsing method always has larger CVs compared to the Complete Collapsing method.

6.5.4 Race summarization of final weighted CVs (Table F.4)
The Race level, final weighted CVs are consistent among the estimation methods. Usually, the No Collapsing method has a higher CV than the Complete Collapsing method. However for “Native Hawaiian and Other Pacific Islander”, this is the opposite. The Complete Collapsing method has a CV of 5.92% and the No Collapsing method has a CV of 5.62%. Finally, across Race, there is no discernable relationship between the CVs and the collapsing parameters.

6.5.5 Employment Status summarization of final weighted CVs (Table F.5)
The Employment Status level, final weighted CVs are consistent among the estimation methods. Of note, the “Armed Forces, with a job but not at work” Employment Status has extremely large CVs among all the methods. The range is between 14.09% and 25.88%. The reason may be the small population. There are only about 4,000 of these people. Finally, across Employment Status, there is no discernable relationship between the CVs and the collapsing parameters. However, the No Collapsing method usually has higher CVs when compared to the Complete Collapsing method. For the “Unemployed” Employment Status, the relationship is vice versa.

6.5.6 Educational Attainment summarization of final weighted CVs (Table F.6)
The Educational Attainment level, final weighted CVs are consistent among the estimation methods. Most of the CVs are under 2.00%. However, the Direct method and the Production method have higher CVs when compared to the collapsing methods, for the “No school completed” Educational Attainment. These CVs are 4.26% for the Direct method, 2.28% for the Production method, and between 1.70% and 1.95% for the collapsing methods. On a different note, often increasing the NAF threshold increases the CV. However for the “No school completed” Educational Attainment, this is not true.

Finally, The No Collapsing method usually has a higher CV when compared to the Complete Collapsing method. However for the "College degree attained" Educational Attainment, this relationship is switched.

6.5.7 Poverty Status summarization of final weighted CVs (Table F.7)
The Poverty Status level, final weighted CVs are consistent among the estimation methods. Most of the CVs are under 2.00%. However, the No Collapsing method consistently has a higher CV when compared to the Complete Collapsing method. Finally, across Poverty Status, there is no discernable relationship between the CVs and the collapsing parameters.

7. Conclusions

In this research the computation method for the GQ NAF is updated. Specifically, a parametrized collapsing algorithm is used to produce localized, yet regulated estimates of the GQ NAF. In addition, the variance methodology for GQs is updated. Replicate factors are applied to GQs on the frame to account for sampling variance on the NAF.

The ACS will begin to implement these experimental methods in production for data year 2019. However, this data will not be available to the public until year 2020.

Two collapsing parameters are used to regulate the amount of collapsing across geography. The NAF threshold regulated the cells' NAF values to be within reasonable bounds. The NSREC parameter regulated the number sampled GQs in a cell. Specifically, it required a cell to have at least a certain number of sampled GQs for reliable estimation. The results showed that increasing the NAF threshold decreases the amount of collapsing. On the other hand, decreasing NSREC decreases the amount of collapsing. The collapsing algorithms spread the estimation cells across the geography levels.

The primary interests are in how the collapsing algorithms and frame variance effect the pre-controlled, GQ coverage rates and GQ population CVs. Specifically, the collapsing algorithm should have an effect on the coverage rates. Yet, the frame variance should not have an effect on the coverage rates. Both the collapsing algorithm and the frame variance should have an effect on the CVs. Most comparisons above the substate level produce coverage rates that are similar among all estimation methods. This includes the GQ type group, and state by GQ type group comparisons. Hence, for these comparisons the collapsing algorithm has little to no effect on the coverage rates.

For the pre-controlled CVs, there are results that are similar among the estimation methods and there are results that are different. At the national level of geography, the collapsing methods produce the largest CVs. However, the differences in CVs are negligible among all methods. At the state level, there are differences among the methods. The parametrized methods have median CVs that are above the current production method's (Production method) median CV. This is because of the frame variance incorporated into the parametrized methods. Yet the parametrized methods have median CVs that are below the Direct method's median CV. This is because of the imputations incorporated into the parametrized methods. Moreover, the state by GQ type group level comparison produces CV distributions that differ between the methods. These results are similar to the state level results. On a different note, the state and state by GQ type group CV distributions produce expected relationships between the collapsing parameters and the CVs. Specifically, when the NAF threshold increases there is an increase in the median CVs. Furthermore, when NSREC decreases there is an increase in the median CVs.

The substate CVs were evaluated at county geography. The research compared the estimation methods' pre-controlled CV and final estimate CV distributions. Specifically, the parametrized methods produce lower median CVs compared to the Direct method and the Production method. The parametrized estimates are more precise because of the imputations, and the localization of the parametrized collapsing algorithms. These two factors diminish the effect the frame replicate weights have on the CVs. On a different note, the No Collapsing method, the Complete Collapsing method, and the parametrized collapsing methods differ in their pre-controlled and final estimate median CVs. The final estimate CV is less than the pre-controlled CV. Finally, the pre-controlled and final estimate CVs have the expected relationship between the collapsing parameters and CVs. That is, when the collapsing parameters favor more collapsing the CVs decrease.

The research compared the characteristic, final population estimates and their CVs among the estimation methods. Across characteristics variables, the population estimates and CVs are consistent. The No Collapsing method usually produces the smallest estimates. Finally, often there is a pattern between the collapsing parameters and the population estimates. The parameters that favor more collapsing produce higher population estimates. For the characteristic CVs, there is usually no discernable relationship between the collapsing patterns and the CVs. However, the No Collapsing method usually has higher CVs than the Complete Collapsing method.In addition, there is no strong indication that the frame replicate weights have an effect on the characteristic CVs.

Overall, collapsing produced consistent population estimates when compared to the Direct method and the Production method. Moreover, for the characteristic population estimates, more collapsing produced larger estimates. On a different note, collapsing and frame variance may produce dissimilar variance among the estimation methods. Dissimilar variances are especially true for levels of analysis with smaller population. Often, more collapsing produces lower variance. This is especially true for levels of analysis with smaller population.

8. Further Research

In the future, the plan is to research the effects of collapsing and frame variance on the 5-year GQ weighting. It is expected that the effects willbe lessened by the averaging of the 5-year data.

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Attachment A: Collapsing patterns for each GQ type group

Table A.1: Collapsing patterns for Correctional Institutions
Data Source: 2016, 1-year, ACS data

Estimation Methodology	National	Region	Division	State
No Collapsing	0	0	0	247
CLPSE 3.5 / 10	154	16	51	26
CLPSE 2 / 10	154	16	59	18
Complete Collapsing	247	0	0	0

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Table A.2: Collapsing patterns for Juvenile Detention Facilities
Data Source: 2016, 1-year, ACS data

Estimation Methodology	National	Region	Division	State
No Collapsing	0	0	0	106
CLPSE 3.5 / 10	4	43	59	0
CLPSE 2 / 10	4	55	47	0
Complete Collapsing	106	0	0	0

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Table A.3: Collapsing patterns for Nursing Homes
Data Source: 2016, 1-year, ACS data

Estimation Methodology	National	Region	Division	State
No Collapsing	0	0	0	116
CLPSE 3.5 / 10	65	0	22	29
CLPSE 2 / 10	65	0	22	29
Complete Collapsing	116	0	0	0

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Table A.4: Collapsing patterns for Other Long-Term Care Facilities
Data Source: 2016, 1-year, ACS data

Estimation Methodology	National	Region	Division	State
No Collapsing	0	0	0	109
CLPSE 3.5 / 10	58	38	13	0
CLPSE 2 / 10	58	38	13	0
Complete Collapsing	109	0	0	0

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Table A.5: Collapsing patterns for College Dormitories
Data Source: 2016, 1-year, ACS data

Estimation Methodology	National	Region	Division	State
No Collapsing	0	0	0	154
CLPSE 3.5 / 10	52	51	13	38
CLPSE 2 / 10	103	0	13	38
Complete Collapsing	154	0	0	0

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Table A.6: Collapsing patterns for Military Facilities
Data Source: 2016, 1-year, ACS data

Estimation Methodology	National	Region	Division	State
No Collapsing	0	0	0	111
CLPSE 3.5 / 10	64	0	47	0
CLPSE 2 / 10	64	25	22	0
Complete Collapsing	111	0	0	0

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Table A.7: Collapsing patterns for Other Non-Institutional Facilities
Data Source: 2016, 1-year, ACS data

Estimation Methodology	National	Region	Division	State
No Collapsing	0	0	0	122
CLPSE 3.5 / 10	18	0	76	28
CLPSE 2 / 10	18	0	76	28
Complete Collapsing	122	0	0	0

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Attachment B: Coverage Rates

Table B.1: GQ type group level, coverage rates
Data Source: 2016, 1-year, ACS data

Estimation Methodology	GQ Type Groups						
	Correctional Institutions	Juvenile Detention Facilities	Nursing Homes	Other Long-Term Care Facilities	College Dormitories	Military Facilities	Other Non-Institutional Facilities
Direct	102.9%	77.08%	90.20%	60.40%	95.66%	70.12%	67.78%
Production	98.59%	77.43%	90.06%	61.57%	96.06%	71.22%	64.56%
No Collapsing	98.47%	78.54%	89.55%	73.51%	96.69%	71.64%	64.54%
CLPSE 3.5 / 5	98.66%	77.00%	90.05%	62.09%	96.08%	71.19%	64.49%
CLPSE 3.5 / 10	98.56%	76.99%	90.05%	61.59%	96.07%	71.19%	64.72%
CLPSE 3.5 / 15	98.55%	76.61%	90.07%	61.54%	96.07%	71.26%	64.67%
CLPSE 2 / 5	98.56%	77.03%	90.05%	61.58%	96.05%	71.23%	64.49%
CLPSE 2 / 10	98.54%	77.03%	90.05%	61.59%	96.04%	71.23%	64.72%
CLPSE 2 / 15	98.55%	76.64%	90.07%	61.54%	96.04%	71.23%	64.67%
Complete Collapsing	98.59%	77.43%	90.06%	61.57%	96.06%	71.22%	64.56%

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Attachment C: GQ Type Group CVs

Table C.1: GQ type group level, pre-controlled CVs
Data Source: 2016, 1-year, ACS data

Estimation Methodology	GQ Type Groups						
	Correctional Institutions	Juvenile Detention Facilities	Nursing Homes	Other Long-Term Care Facilities	College Dormitories	Military Facilities	Other Non-Institutional Facilities
Direct	1.49%	7.60%	1.32%	11.55%	0.86%	5.30%	2.54%
Production	0.91%	1.81%	0.54%	3.38%	0.65%	2.27%	0.91%
No Collapsing	1.06%	7.37%	1.88%	7.41%	1.81%	5.86%	2.89%
CLPSE 3.5 / 5	1.09%	6.97%	1.68%	11.59%	1.63%	6.37%	2.86%
CLPSE 3.5 / 10	1.10%	7.20%	1.69%	12.04%	1.62%	6.37%	2.91%
CLPSE 3.5 / 15	1.11%	7.01%	1.69%	11.99%	1.62%	6.43%	2.86%
CLPSE 2 / 5	1.10%	6.99%	1.68%	12.02%	1.57%	6.44%	2.87%
CLPSE 2 / 10	1.11%	7.23%	1.69%	12.04%	1.57%	6.44%	2.91%
CLPSE 2 / 15	1.11%	7.04%	1.69%	11.99%	1.57%	6.44%	2.86%
Complete Collapsing	1.12%	7.45%	1.70%	12.60%	1.60%	6.61%	3.17%

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Attachment D: County level CVs

Table D.1: County level, pre-controlled, CV percentiles
Data Source: 2016, 1-year, ACS data

Estimation Methodology	CV percentiles				
	Min	P25	P50	P75	Max
Direct	4.68%	26.35%	51.57%	99.98%	108.3%
Production	2.29%	20.72%	39.33%	66.38%	140.0%
No Collapsing	0.00%	4.06%	6.30%	10.36%	200.0%
CLPSE 3.5 / 5	0.00%	3.71%	6.01%	9.66%	200.0%
CLPSE 3.5 / 10	0.00%	3.28%	5.25%	8.29%	200.0%
CLPSE 3.5 / 15	0.00%	3.22%	5.13%	7.93%	200.0%
CLPSE 2 / 5	0.00%	3.56%	5.71%	8.75%	200.0%
CLPSE 2 / 10	0.00%	3.18%	5.08%	7.90%	200.0%
CLPSE 2 / 15	0.00%	3.12%	4.95%	7.64%	200.0%
Complete Collapsing	0.00%	1.20%	1.81%	3.08%	200.0%

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Table D.2: County level, final estimate, CV percentiles
Data Source: 2016, 1-year, ACS data

Estimation Methodology	CV percentiles				
	Min	P25	P50	P75	Max
Direct	0.00%	26.62%	51.77%	98.38%	207.4%
Production	0.00%	20.29%	38.14%	65.63%	222.5%
No Collapsing	0.00%	2.35%	3.97%	7.41%	200.0%
CLPSE 3.5 / 5	0.00%	2.14%	3.54%	6.23%	200.0%
CLPSE 3.5 / 10	0.00%	1.92%	3.12%	5.33%	200.0%
CLPSE 3.5 / 15	0.00%	1.90%	3.05%	5.06%	200.0%
CLPSE 2 / 5	0.00%	1.90%	3.20%	5.39%	200.0%
CLPSE 2 / 10	0.00%	1.77%	2.90%	4.91%	200.0%
CLPSE 2 / 15	0.00%	1.76%	2.86%	4.82%	200.0%
Complete Collapsing	0.00%	0.86%	1.41%	2.70%	200.0%

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Attachment E: Characteristic Final Population Estimates

Table E.1: Sex level, final population estimates
Data Source: 2016, 1-year, ACS data

Estimation Methodology	Sex	
	Male	Female
Direct	4,866,000	3,253,000
Production	4,948,000	3,171,000
No Collapsing	4,656,000	2,994,000
CLPSE 3.5 / 5	4,742,000	3,042,000
CLPSE 3.5 / 10	4,761,000	3,053,000
CLPSE 3.5 / 15	4,785,000	3,077,000
CLPSE 2 / 5	4,759,000	3,053,000
CLPSE 2 / 10	4,767,000	3,059,000
CLPSE 2 / 15	4,792,000	3,081,000
Complete Collapsing	4,948,000	3,171,000

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Table E.2: Age group level, final population estimates
Data Source: 2016, 1-year, ACS data

Estimation Methodology	Age groups									
	08 or less	09 to 16	17 to 24	25 to 32	33 to 40	41 to 48	49 to 56	57 to 64	65 to 72	73 or greater
Direct	21,980	106,900	3,414,000	860,100	692,000	526,900	518,400	415,400	330,900	1,233,000
Production	22,870	108,700	3,414,000	859,100	690,700	525,200	527,100	436,000	327,100	1,209,000
No Collapsing	19,090	88,760	3,243,000	808,500	652,200	491,000	487,100	399,900	308,100	1,152,000
CLPSE 3.5 / 5	19,600	94,230	3,314,000	822,200	659,700	496,300	491,900	404,100	312,700	1,169,000
CLPSE 3.5 / 10	20,120	95,480	3,320,000	825,100	662,400	498,900	495,700	406,200	314,600	1,176,000
CLPSE 3.5 / 15	20,410	95,350	3,323,000	829,900	667,900	504,600	503,400	413,900	316,700	1,187,000
CLPSE 2 / 5	19,700	94,200	3,325,000	825,300	662,100	498,500	494,500	406,600	313,800	1,172,000
CLPSE 2 / 10	20,120	95,540	3,330,000	825,800	663,000	499,100	496,000	406,300	314,600	1,176,000
CLPSE 2 / 15	20,400	95,520	3,335,000	830,100	668,100	504,700	503,500	413,900	316,800	1,187,000
Complete Collapsing	22,870	108,700	3,414,000	859,100	690,700	525,200	527,100	436,000	327,100	1,209,000

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Table E.3: Hispanic origin level, final population estimates
Data Source: 2016, 1-year, ACS data

Estimation Methodology	Hispanic origin	
	Not Hispanic	Hispanic
Direct	7,027,000	1,093,000
Production	7,011,000	1,108,000
No Collapsing	6,600,000	1,050,000
CLPSE 3.5 / 5	6,720,000	1,063,000
CLPSE 3.5 / 10	6,749,000	1,065,000
CLPSE 3.5 / 15	6,791,000	1,072,000
CLPSE 2 / 5	6,748,000	1,064,000
CLPSE 2 / 10	6,761,000	1,066,000
CLPSE 2 / 15	6,803,000	1,073,000
Complete Collapsing	7,011,000	1,108,000

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Table E.4: Race level, final population estimates
Data Source: 2016, 1-year, ACS data

Estimation Methodology	Race				
	White	Black	American Indian and Alaska Native	Asian	Native Hawaiian and Other Pacific Islander
Direct	5,613,000	1,771,000	97,490	361,800	20,320
Production	5,551,000	1,825,000	95,480	363,100	22,790
No Collapsing	5,219,000	1,730,000	87,630	344,500	21,070
CLPSE 3.5 / 5	5,315,000	1,757,000	89,270	350,200	21,270
CLPSE 3.5 / 10	5,338,000	1,761,000	90,230	351,000	21,670
CLPSE 3.5 / 15	5,372,000	1,767,000	91,540	356,500	22,410
CLPSE 2 / 5	5,336,000	1,762,000	89,700	350,600	21,250
CLPSE 2 / 10	5,347,000	1,764,000	90,320	351,300	21,590
CLPSE 2 / 15	5,382,000	1,769,000	91,730	356,800	22,260
Complete Collapsing	5,551,000	1,825,000	95,480	363,100	22,790

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Table E.5: Employment status level, final population estimates
Data Source: 2016, 1-year, ACS data

Estimation Methodology	Employment Status					
	Employed, at work	Employed, with a job but not at work	Unemployed	Armed Forces, at work	Armed Forces, with a job but not at work	Not in labor force
Direct	1,149,000	87,590	213,400	307,300	4,972	6,272,000
Production	1,156,000	90,060	225,900	314,700	3,798	6,240,000
No Collapsing	1,067,000	85,020	208,200	285,600	3,668	5,928,000
CLPSE 3.5 / 5	1,090,000	86,650	211,300	304,200	3,930	6,012,000
CLPSE 3.5 / 10	1,096,000	86,850	212,800	304,200	3,930	6,033,000
CLPSE 3.5 / 15	1,109,000	87,040	215,100	302,500	3,852	6,067,000
CLPSE 2 / 5	1,099,000	87,410	213,200	302,400	3,796	6,030,000
CLPSE 2 / 10	1,101,000	87,400	213,400	302,400	3,796	6,040,000
CLPSE 2 / 15	1,114,000	87,590	215,700	302,400	3,796	6,074,000
Complete Collapsing	1,156,000	90,060	225,900	314,700	3,798	6,240,000

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Table E.6: Educational attainment level, final population estimates
Data Source: 2016, 1-year, ACS data

Estimation Methodology	Educational Attainment			
	No school completed	Some school but no high school diploma	High school graduate but no college degree	College degree attained
Direct	142,800	1,531,000	5,691,000	747,900
Production	139,600	1,533,000	5,684,000	755,300
No Collapsing	120,000	1,429,000	5,393,000	701,000
CLPSE 3.5 / 5	122,700	1,453,000	5,487,000	715,200
CLPSE 3.5 / 10	123,900	1,461,000	5,504,000	719,000
CLPSE 3.5 / 15	126,500	1,472,000	5,528,000	729,000
CLPSE 2 / 5	123,300	1,458,000	5,507,000	718,500
CLPSE 2 / 10	123,900	1,462,000	5,514,000	719,900
CLPSE 2 / 15	126,500	1,472,000	5,541,000	729,100
Complete Collapsing	139,600	1,533,000	5,684,000	755,300

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Table E.7: Poverty Status level, final population estimates
Data Source: 2016, 1-year, ACS data

Estimation Methodology	Poverty Status	
	Not in poverty	In poverty
Direct	373,100	747,400
Production	364,600	759,200
No Collapsing	297,100	641,000
CLPSE 3.5 / 5	303,400	650,900
CLPSE 3.5 / 10	307,600	661,400
CLPSE 3.5 / 15	328,400	688,600
CLPSE 2 / 5	307,400	662,200
CLPSE 2 / 10	307,600	661,400
CLPSE 2 / 15	328,400	688,600
Complete Collapsing	364,600	759,200

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Attachment F: Characteristic Final Population CVs

Table F.1: Sex level, final population CVs
Data Source: 2016, 1-year, ACS data

Estimation Methodology	Sex	
	Male	Female
Direct	0.42%	0.63%
Production	0.23%	0.36%
No Collapsing	0.23%	0.39%
CLPSE 3.5 / 5	0.27%	0.41%
CLPSE 3.5 / 10	0.24%	0.38%
CLPSE 3.5 / 15	0.20%	0.34%
CLPSE 2 / 5	0.26%	0.39%
CLPSE 2 / 10	0.24%	0.37%
CLPSE 2 / 15	0.22%	0.32%
Complete Collapsing	0.22%	0.34%

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Table F.2: Age group level, final population CVs
Data Source: 2016, 1-year, ACS data

Estimation Methodology	Age groups									
	08 or less	09 to 16	17 to 24	25 to 32	33 to 40	41 to 48	49 to 56	57 to 64	65 to 72	73 or greater
Direct	11.30%	3.56%	0.28%	1.06%	1.18%	1.31%	1.33%	1.63%	2.08%	1.05%
Production	6.87%	1.85%	0.18%	0.80%	0.95%	1.33%	1.13%	1.05%	1.32%	0.47%
No Collapsing	4.72%	1.80%	0.36%	0.88%	1.05%	0.99%	1.29%	1.13%	1.01%	0.51%
CLPSE 3.5 / 5	4.54%	1.89%	0.20%	0.88%	0.98%	1.06%	1.07%	1.22%	1.04%	0.30%
CLPSE 3.5 / 10	4.53%	1.64%	0.21%	0.78%	0.94%	1.12%	1.23%	1.14%	1.03%	0.30%
CLPSE 3.5 / 15	4.49%	1.78%	0.22%	0.82%	0.95%	1.13%	1.16%	1.14%	0.96%	0.32%
CLPSE 2 / 5	5.04%	1.94%	0.21%	0.84%	0.94%	0.94%	1.07%	1.24%	1.04%	0.28%
CLPSE 2 / 10	4.85%	1.71%	0.19%	0.89%	0.87%	1.07%	1.14%	1.24%	1.19%	0.28%
CLPSE 2 / 15	4.81%	1.81%	0.19%	0.84%	0.88%	1.07%	1.14%	1.31%	1.09%	0.36%
Complete Collapsing	4.45%	1.55%	0.17%	0.73%	0.85%	1.17%	1.16%	1.05%	1.22%	0.32%

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Table F.3: Hispanic origin level, final population CVs
Data Source: 2016, 1-year, ACS data

Estimation Methodology	Hispanic origin	
	Not Hispanic	Hispanic
Direct	0.18%	1.15%
Production	0.12%	0.78%
No Collapsing	0.19%	0.70%
CLPSE 3.5 / 5	0.16%	0.75%
CLPSE 3.5 / 10	0.13%	0.63%
CLPSE 3.5 / 15	0.14%	0.69%
CLPSE 2 / 5	0.13%	0.73%
CLPSE 2 / 10	0.13%	0.70%
CLPSE 2 / 15	0.13%	0.68%
Complete Collapsing	0.10%	0.63%

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Table F.4: Race level, final population CVs
Data Source: 2016, 1-year, ACS data

Estimation Methodology	Race				
	White	Black	American Indian and Alaska Native	Asian	Native Hawaiian and Other Pacific Islander
Direct	0.31%	0.88%	3.05%	1.80%	6.89%
Production	0.21%	0.60%	2.81%	1.28%	5.93%
No Collapsing	0.26%	0.57%	2.73%	1.70%	5.62%
CLPSE 3.5 / 5	0.19%	0.51%	3.30%	1.68%	5.91%
CLPSE 3.5 / 10	0.19%	0.52%	3.00%	1.46%	7.58%
CLPSE 3.5 / 15	0.20%	0.55%	2.73%	1.42%	5.20%
CLPSE 2 / 5	0.23%	0.57%	2.91%	1.66%	6.49%
CLPSE 2 / 10	0.19%	0.46%	2.55%	1.29%	6.50%
CLPSE 2 / 15	0.22%	0.52%	2.46%	1.19%	6.20%
Complete Collapsing	0.18%	0.52%	2.55%	1.33%	5.92%

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Table F.5: Employment status level, final population CVs
Data Source: 2016, 1-year, ACS data

Estimation Methodology	Employment Status					
	Employed, at work	Employed, with a job but not at work	Unemployed	Armed Forces, at work	Armed Forces, with a job but not at work	Not in labor force
Direct	1.16%	3.46%	2.67%	1.14%	25.88%	0.23%
Production	0.77%	2.46%	2.31%	0.80%	17.16%	0.14%
No Collapsing	0.74%	3.24%	1.90%	1.07%	18.00%	0.22%
CLPSE 3.5 / 5	0.71%	2.93%	1.88%	0.87%	17.44%	0.16%
CLPSE 3.5 / 10	0.79%	2.88%	1.76%	0.80%	16.53%	0.17%
CLPSE 3.5 / 15	0.73%	2.75%	1.96%	0.84%	16.92%	0.15%
CLPSE 2 / 5	0.80%	3.03%	1.72%	0.86%	14.09%	0.16%
CLPSE 2 / 10	0.59%	3.01%	1.90%	0.72%	15.64%	0.15%
CLPSE 2 / 15	0.67%	2.83%	2.10%	0.76%	16.49%	0.15%
Complete Collapsing	0.60%	2.72%	2.31%	0.80%	17.09%	0.12%

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Table F.6: Educational attainment level, final population CVs
Data Source: 2016, 1-year, ACS data

Estimation Methodology	Educational Attainment			
	No school completed	Some school but no high school diploma	High school graduate but no college degree	College degree attained
Direct	4.26%	0.84%	0.23%	1.37%
Production	2.28%	0.52%	0.17%	1.02%
No Collapsing	1.95%	0.54%	0.22%	0.91%
CLPSE 3.5 / 5	1.70%	0.50%	0.21%	1.00%
CLPSE 3.5 / 10	1.84%	0.52%	0.20%	0.96%
CLPSE 3.5 / 15	1.82%	0.56%	0.20%	0.98%
CLPSE 2 / 5	1.71%	0.50%	0.17%	0.88%
CLPSE 2 / 10	1.92%	0.47%	0.17%	0.94%
CLPSE 2 / 15	1.78%	0.46%	0.18%	0.85%
Complete Collapsing	1.80%	0.48%	0.16%	0.93%

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Table F.7: Poverty Status level, final population CVs
Data Source: 2016, 1-year, ACS data

Estimation Methodology	Poverty Status	
	Not in poverty	In poverty
Direct	2.65%	1.34%
Production	1.32%	0.65%
No Collapsing	0.93%	0.75%
CLPSE 3.5 / 5	0.72%	0.69%
CLPSE 3.5 / 10	0.74%	0.62%
CLPSE 3.5 / 15	0.90%	0.63%
CLPSE 2 / 5	0.85%	0.70%
CLPSE 2 / 10	0.91%	0.70%
CLPSE 2 / 15	0.89%	0.64%
Complete Collapsing	0.79%	0.38%

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