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# Review of the FoodAPS 2012 Sample Design


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Maitland, A., and Li, L. (2016). *Review of the Completeness and Accuracy of FoodAPS 2012 Data.* Prepared for the Economic Research Service, U.S. Department of Agriculture. Washington, D.C.

Petraglia, E., Van de Kerckhove, W., and Krenzke, T. (2016). *Review of the Potential for Nonresponse Bias in FoodAPS 2012.* Prepared for the Economic Research Service, U.S. Department of Agriculture. Washington, D.C.

Yan, T., and Maitland, A. (2016). *Review of the FoodAPS 2012 Instrument Design, Response Burden, Use of Incentives, and Response Rates.* Prepared for the Economic Research Service, U.S. Department of Agriculture. Washington, D.C.

# Executive Summary

The 2012 National Household Food Acquisition and Purchase Survey (FoodAPS) (hereafter referred to as "FoodAPS-1") is a household survey fielded primarily in 2012 and designed to capture detailed information on the food acquisitions of U.S. households. FoodAPS-1 was sponsored by the U.S. Department of Agriculture (USDA) and managed by its Economic Research Service (ERS). In 2015, ERS contracted with Westat to conduct an independent assessment of the quality of the FoodAPS-1 sample design, instrumentation, data collection procedures, and resulting data. This report is part of a series of five reports that constitute that assessment.

This report presents an evaluation of the sample design for FoodAPS-1. The evaluation focused on the resulting precision of estimates and the sources of impact that may cause the variances to be higher than expected. The FoodAPS-1 survey was designed by the survey contractor Mathematica Policy Research (Mathematica) to provide nationally representative estimates of adequate precision of food expenditures and other outcome variables for certain target groups, and to conduct comparisons with minimum detectable differences. The key domains of interest, referred to as target groups, were defined as:

> Group A. Households with income less than the poverty guideline not receiving Supplemental Nutrition Assistance Program (SNAP) benefits;
>
> Group B. Households with income greater than or equal to 100 percent and less than 185 percent of the poverty guideline not receiving SNAP benefits;
>
> Group C. Households with income greater or equal to 185 percent of the poverty guideline not receiving SNAP benefits; and
>
> Group D. Households receiving SNAP benefits.

An important objective was to compare food acquisitions for (1) SNAP and non-SNAP households; (2) SNAP and non-participating SNAP-eligible households; and (3) all low-income (SNAP and non-SNAP) and higher income households. Of interest is to understand the reasons some low-income households do not participate in government programs such as SNAP.

The sampling plan took into account the complex features of the design, including assumptions on the impact that clustering and differential sampling rates (and sampling weights) would have on the precision of estimates. This impact on variances is commonly addressed through estimating design effects. The design effect is the increase in sample size needed under a complex design (which

includes clustering, differential sampling rates, stratification) in order to achieve the same precision under simple random sampling. The effective sample size is the actual sample size divided by the design effect. It reflects the sample size under simple random sampling that is needed to attain the precision that resulted from the complex design.

Westat examined the impact of the sample design on the precision of some key survey estimates for each target group individually and also for comparisons between the groups. The outcomes evaluated were (1) total amount spent on food consumed at home (FAH) events, (2) total spent on food away from home (FAFH) events, (3) total number of free events, and (4) a measure of food insecurity. The subgroups of interest for the evaluation included (1) the four target groups, (2) Special Supplemental Nutrition Program For Women, Infants, and Children (WIC) household classification, (3) metro/non-metro classification (designated by county), and (4) rural/non-rural classification (designated by Census tract).

The contractor provided broad ranges of the expected precision in terms of the design effect, effective sample sizes, and minimum detectable differences (MDDs) that are used when making comparisons between two subgroups. In general, the resulting measures of precision look reasonable at the national level (i.e., for the total sample). The effective sample sizes exceeded the upper bound on the range of expected effective sample size for two of the four outcome measures. For Target Group C, while the actual sample size surpassed the targeted sample size, the upper bound of the effective sample size was exceeded by two of the outcome measures, however, for one outcome measure the effective sample size was closer to the lower bound. For SNAP (Target Group D), while the actual sample size was about the same as planned, the effective sample size was closer to the lower bound for two (and marginally for three) of the outcome measures. When comparing groups with the largest sample sizes, that is, comparing Target Group C with Target Groups A, B, and D, the actual MDD was sometimes lower than the expected MDD lower bound.

It is for the smaller subgroups, such as the Target Groups A and B, where effective sample sizes were smaller than desired for FAH and FAFH expenditures, and where sample design improvements may be helpful. That being said, although these effective sample sizes were smaller than expected, when making comparisons with Target Group D, the large sample size in Target Group D helped the resulting actual MDDs to fall into the broad range of expected MDDs.

The results in terms of total variance and variance components from a prior survey usually can help improve the sample design in future cycles of the survey, leading to larger effective sample sizes for subgroup analyses. The total variance can be decomposed into components of variance (such as the

impact due to differential sampling rates [or weights], clustering, and stratification) so that reasons for larger unexpected variation can be determined. This report investigates the components of variance toward improving the sample design for the next main survey of FoodAPS.

In this review of the sample design, larger-than-expected variability in the weights was observed, which impacted the resulting precision of estimates. Variability across target groups is by design, but a great amount of within-group variability is problematic. Part of the weight variation issue is misclassification (discussed below), and the way the sample was released. Also, the design proved challenging as illustrated by the actual sample sizes for Target Groups A and B falling far short of the target sample sizes.

As mentioned above, one particular point of focus is on misclassification of the target groups. Households were classified into target groups at three different points in time:

- SNAP list designation at the time of sampling addresses within Secondary Sampling Units (SSUs);
- Classification based on responses to the screener; and
- Classification based on responses to the initial interview, combined with a second more-timely SNAP list match, and imputation due to nonresponse to the interview.

The switching of target group classifications between their SNAP list designation and their screener classification, and between the screener classification and the initial interview (combined with a second, more timely SNAP list match and imputations), can have an increasing effect on the variation of weights. That is, when analyzing a group of records from within a final target group designation, the respondents arrive in that group by several different ways, varying widely as to their probabilities of selection, which causes variation among the weights. Table ES-1 demonstrates the level of agreement between the target group assigned at the screener at the final target group designation from the main study. Agreement between the two target group assignments is quite low, at 64 percent overall. Agreement is highest with Target Group D (those on the SNAP list) with 84 percent agreement. All other group assignments are quite poor, ranging from 52 to 60 percent agreement between the two target group assignments with Target Group C having the lowest rates of agreement.

Table ES-1. Main study target group assignment and screener target group assignment agreement

| Main study target group assignment | Screener target group assignment | Frequency | In-cell agreement | Overall agreement |
|---|---|---|---|---|
| A | A | 173 | 57% | 64% |
| A | B | 103 | | |
| A | C | 12 | | |
| A | D | 14 | | |
| B | A | 232 | 60% | |
| B | B | 445 | | |
| B | C | 51 | | |
| B | D | 17 | | |
| C | A | 157 | 52% | |
| C | B | 664 | | |
| C | C | 903 | | |
| C | D | 19 | | |
| D | A | 110 | 84% | |
| D | B | 106 | | |
| D | C | 17 | | |
| D | D | 1,188 | | |

**Note:** This table was process for the 22 states with PSU sample that provided SNAP lists.

Consistency of the screener target group assignment with designations from the SNAP list and the main survey can have a large impact on weight variation and, consequently, on the variances of the estimates. Therefore, as explained above, there is a lot of weight variation within the main study target group assignment. The standard deviation of the weights is larger than the mean for every target group. The maximum weight in target group ranges from 7.5 to 11.7 times the mean for that cell. This misclassification and its impact on variances are explored further in the report.

After a review of the sample design that was implemented, three main aspects of the design were studied: (1) stratification, (2) clustering, and (3) weight variation, where the first one has potential to decrease the variance, and the last two introduce an increase in variance.

In general, as seen in Table ES-2, the stratification impact results were mixed; however, future design work should explore the benefits of explicit stratification of Primary Sampling Units (PSUs) versus the use of the composite measure of size (MOS). The composite MOS is used to select PSUs and SSUs with probability proportionate-to-size. The MOS is a function of planned sampling rates and estimated population in each target group. The numerator of the impact ratio includes the strata in the estimates of variance. The denominator is the variance computed without using the strata in the computations. Lower values of the index indicate that stratification had a greater effect in lowering standard errors. The ratio that is used as the evaluation measure is likely to overstate the impact (i.e., be lower) because the denominator is likely an overestimate. That is, the units were

selected with implicit stratification, and so the FoodAPS-1 PSUs are dispersed more than if selected without stratification.

**Table ES-2. Impact ratio due to stratification for outcome measures**

| Outcome/ statistic of interest | Estimate | Standard error (with stratification) | Standard error (without stratification) | Impact ratio |
|---|---|---|---|---|
| Average Spent on FAH | $105.72 | 2.90 | 3.48 | 0.69 |
| Average Spent on FAFH | $56.52 | 1.61 | 2.64 | 0.37 |
| Average Number of Free Events | 3.02 | 0.14 | 0.11 | 1.53 |
| Proportion Food Insecurity | 0.16 | 0.01 | 0.01 | 0.79 |

The sorting variables used in FoodAPS-1 were metro status and Food and Nutrition Service (FNS) region. Use of other potential stratification variables, such as percentage in poverty, may provide a better chance at arriving at desired sample sizes for Target Groups A (where a shortfall occurred) and B, and may provide more potential to reduce the resulting variance to get more power out of the survey cases. Future design work should explore the benefits of using the composite MOS, as well as the best sources for the stratification and MOS variables.

The clustering amounts in FoodAPS-1 are about as expected, as shown in Table ES-3. The sizes of the FoodAPS-1 PSUs and SSUs are among the largest in use by in-person surveys in terms of both geographic and population size, which results in low impact on variances from clustering. That is, observations within a PSU or SSU are not as correlated among households than if smaller geographic areas were formed. However, the geographic size also increases travel time by interviewers and may increase costs as well as decrease response rates. In terms of PSUs and SSUs, future design work should:

- Incorporate the estimated intracluster correlations shown in Table ES-3 to gauge the number to select. The expected intraPSU correlations were expected to be between 0.01 and 0.05. The estimated correlations among the survey outcomes variables were in that range. This report also extends the investigation into subgroups (i.e., WIC), and intraSSU correlations, which range from 0.05 to 0.10, sometimes a bit higher;
- Take into consideration response rates and interviewer travel time when determining other ways to form PSUs; and
- Consider the number of degrees of freedom for statistical analysis because it is related to the number of first-stage units. That is, increasing the number of PSUs will increase the degrees of freedom, which provides greater stability of variances especially among subgroups, which reduces the widths of confidence intervals, and it allows for better estimates of the clustering impact.

Table ES-3. Intracluster correlations for Primary Sampling Units (PSUs) and Secondary Sampling Units (SSUs)

| Outcome/statistic | Intracluster correlation | |
|---|---|---|
| | IntraPSU correlation ($\rho_1$) | IntraSSU correlation ($\rho_2$) |
| Average Spent on FAFH | 0.00 | 0.05 |
| Average Spent on FAH | 0.01 | 0.10 |
| Average Number of Free Events | 0.02 | 0.08 |
| Proportion Food Insecurity | 0.02 | 0.10 |

Among the three main aspects that impact the resulting variances, the most potential for improvement lies in reducing the weight variation. Future design work should ensure protocols to eliminate or limit the increased amount of weight variation when handling drop points in the address lists, updating the address lists for new construction or coverage issues with the lists, and addressing shortfalls in sample yield, especially when releasing reserve sample. Ways should be sought to reduce weight variation within target groups through the sampling process (especially release of replicates) and to minimize screener misclassification. As mentioned above, a large contributor to weight variation is misclassification among the target groups. In addition, other domains, such as incorporating WIC in the definition of target groups, will be explored with the assignment of sampling rates in the sampling plan for the next main survey.

# Overview 1

The 2012 National Household Food Acquisition and Purchase Survey (hereafter referred to as "FoodAPS-1") gathered detailed information about household food acquisitions from April 2012 to mid-January 2013. The survey was sponsored by the U.S. Department of Agriculture (USDA) and developed and fielded by Mathematica Policy Research (Mathematica). The nationally representative sample consisted of nearly 5,000 households that completed the FoodAPS-1 final interview. In 2015, Economic Research Service (ERS) of USDA contracted with Westat to conduct an independent assessment of the quality of the FoodAPS-1 sample design, instrumentation, data collection procedures, and resulting data. This report is part of a series of five reports that constitute that assessment. As part of the effort, Westat conducted an independent assessment of the sample design for the FoodAPS-1. This document presents the results of the evaluation of the FoodAPS-1 sample design.

## 1.1 FoodAPS-1 Analytic Objectives

The FoodAPS-1 survey was designed to provide nationally representative estimates of adequate precision of expenditures for both food at home (FAH) and food away from home (FAFH), as well as other outcome variables for certain target groups. The target groups were defined in terms of participation in the Supplemental Nutrition Assistance Program (SNAP), household size, and total reported household income (which was used in determining a household's income in relation to the poverty guidelines), namely:

A. Households with income less than the poverty guideline not receiving SNAP benefits;

B. Households with income greater than or equal to 100 percent and less than 185 percent of the poverty guideline not receiving SNAP benefits;

C. Households with income greater or equal to 185 percent of the poverty guideline not receiving SNAP benefits, and

D. Households receiving SNAP benefits.

Another important objective was to compare food acquisitions for (1) SNAP and non-SNAP households; (2) SNAP and non-participating SNAP-eligible households; and (3) all low-income

(SNAP and non-SNAP) and higher income households. Of interest is to understand the reasons some low-income household do not participate in government programs, such as SNAP.
We examine the impact of the sample design on the precision of some key survey estimates for each target group individually and also for comparisons between the groups. The outcomes of interest were:

- Total amount spent on food consumed at home (FAH) events (derived from TOTALPAID for FAH);
- Total spent on food away from home (FAFH) events (derived from TOTALPAID for FAFH);
- Total number of free events (derived from FREE for FAH and FAFH), and
- Indicator for food insecurity (defined as having low or very low food insecurity, derived from ADLTFSCAT).

The subgroups of interest were:

- Target groups;
- Special Supplemental Nutrition Program For Women, Infancts, and Children (WIC) household classification;
- Metro/non-metro classification (designated by county); and
- Rural/non-rural classification (designated by Census tract).

The sample design plan took into account complex features, including assumptions on the impact that clustering and differential sampling rates (and sampling weights) would have on the precision of estimates. This impact on variances is commonly addressed through estimating design effects. The design effect is the increase in sample size needed under a complex design (includes clustering, differential sampling rates, stratification) in order to achieve the same precision under simple random sampling. The effective sample size is the actual sample size divided by the design effect. It reflects the sample size under simple random sampling to attain the precision that resulted from the complex design. This report provides actual design effects and effective sample sizes, and explores the reasons why some results were not as expected.

One particular point of focus is on misclassification. Households were classified into target groups at three different points in time:

1. SNAP list designation at the time of sampling addresses within secondary sampling units (SSUs);
2. Classification based on responses to the screener; and
3. Classification based on responses to the initial interview, combined with a second, more timely SNAP list match, and imputation due to nonresponse to the interview.

The switching of target group classifications between their SNAP list designation and their screener classification, and between the screener classification and the initial interview (combined with a second, more timely SNAP list match and imputations), can have an increasing effect on the variation of weights. This misclassification (sometimes referred to as stratum jumping) and its impact on variances are explored further.

## 1.2 Description of FoodAPS-1 Sample Design

FoodAPS-1 employed a stratified three-stage cluster sample design. All areas in the contiguous United States had a non-zero probability of selection. The stages of selection included:

1. 50 primary sampling units (PSUs), where the PSUs were single counties or groups of counties;
2. 8 SSUs per PSU, where the SSUs were block groups; and
3. A sample of addresses within each SSU, with all households at selected addresses being included in the screening phase of the survey.

As shown in Table 1-1, the target sample sizes for Target Groups A through D were 800 (16% of the total sample), 1,200 (24%), 1,500 (30%), and 1,500 (30%), respectively. An estimated population distribution is provided. The estimated population proportions for A and D are extracted from Table 3.6 in the internal draft Survey Design report (Cole, et al., 2016) written by Mathematica, hereafter referred to as the "Mathematica Design Report." Mathematica explains that

> The SNAP measure used for post-stratification is RSNAPNow (the respondent report of SNAP on the Initial Interview adjusted by the results of the administrative match). Note: External control totals are weighted counts from the 2013 CPS, except for "SNAP Participation and Poverty

Level" and "Whether one or more people 60 years and over reside in household," which are based on the 2012 ACS data adjusted to match the 2013 CPS total number of households.

The national percentages reported for Target Groups A, combined B/C, and D were 7.6 percent, 78.8 percent, and 13.6 percent, respectively. The estimated combined total for B and C was reported, and we used proportional allocation using the estimated population proportions in Hall, Denbaly, and Weidman (2012) to estimate the percentages in B and C. The large amount of oversampling conducted for Target Groups A, B and D reflects the objectives of FoodAPS-1 and the high interest in those subgroups, as well as the comparisons among them.

**Table 1-1. Distribution of population and planned sample by target group**

| Target group | Estimated population distribution (survey design report) (%)* | Planned | |
|---|---|---|---|
| | | Sample size | Percent (%) |
| A | 7.6 | 800 | 16.0 |
| B | 12.7 | 1,200 | 24.0 |
| C | 66.0 | 1,500 | 30.0 |
| D | 13.6 | 1,500 | 30.0 |
| Total | 100 | 5,000 | 100.0 |

* The estimated population proportions for A and D are extracted from Mathematica's draft Survey Design report. The estimated combined total for B and C was reported, and we used proportional allocation using the estimated population proportions in Hall, Denbaly and Weidman (2012) to estimate the percentages in B and C.

### *Selection of PSUs*

The first stage of selection involved the formation of the PSUs and the assignment of a measure of size (MOS) to be used in sampling the PSUs with probability proportional to size (PPS). The PSUs were divided into strata (certainty and non-certainty), and non-certainty PSUs were selected by PPS using implicit stratification.

There were 948 PSUs formed within the contiguous United States by using data from the Public Use Microdata Sample (PUMS) from the 3-year American Community Survey (ACS) (2006–08). The PUMS records were identified with Public Use Microdata Areas (PUMAs), which have at least 100,000 people. The FoodAPS-1 PSUs were mainly (1) single counties, (2) groups of counties in a PUMA, or (3) groups of PUMAs sharing counties. In this manner, the PUMS estimates at the PUMA level could be combined with the county-based SNAP file to help form the MOS when

selecting PSUs. We also note that some Metropolitan Statistical Areas (MSA)[1] were split into multiple PSUs.

The sources for the data used to derive the MOS were the 2006–08 3-year ACS PUMS and a list of counties with estimated total population and SNAP participants compiled by the *New York Times* (NYT). The NYT data were obtained from state SNAP agencies.[2] The derivation of the estimated number of households in each target group was complex. The Mathematica Design Report's Appendix B outlines the steps to create PSU-level estimates of 2009 household counts, as follows:

- Used the PUMS files to create estimates of average number of persons per household for the SNAP and non-SNAP groups;
- Used these estimates of persons per household to create estimates of numbers of 2009 SNAP and non-SNAP households in the different target groups; and
- Adjusted the PUMs 2008 estimated totals for households to match our estimate of 2009 households by SNAP and non-SNAP status.

Following Folsom et al. (1987), the MOS assigned to each PSU was a function of the estimated number of households in each target group and the overall sampling rates of addresses within the PSU for each target group. The goal of assigning the MOS in this manner was to arrive at the target sampling rates by target group, and to arrive at equal selection probabilities within groups.

Due to a large MOS, there was one PSU identified as a certainty selection (probability of selection equal to one). As described in Hall, Denbaly, and Weidman (2012), the other 49 PSUs were selected with probability proportionate to MOS from the remaining 947 non-certainty PSUs (specifically, Chromy's method of sequential random sampling was used as available in SAS Proc SurveySelect). Prior to selection, the PSUs were sorted by metropolitan status and region (as defined below). Using a sort order introduces an implicit stratification, which is done to help reduce the variances of survey estimates. The metropolitan status was (1) metro, (2) non-metro, or (3) mixed (included counties in an MSA and counties not in an MSA). Among the sample of 50 PSUs, 34 were metro PSUs, 10 were non-metro PSUs, and 6 were mixed PSUs. Region was defined by 7 USDA Food and Nutrition Service (FNS) administrative regions, as shown in Table 1-2. The number of selected PSUs in each FNS region varied from 4 to 11. An investigation of the stratification impact is explored in Chapter 4.

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[1] See *Federal Register*, Vol. 75, No. 123, June 28, 2010, for more information.

[2] Accessed at http://www.nytimes.com/interactive/2009/11/28/us/20091128-foodstamps.html.

Table 1-2. Definition of USDA Food and Nutrition Service (FNS) Administrative Regions

| Region | States/Territories included in FNS administrative regions |
|---|---|
| Mid-Atlantic | Delaware, District of Columbia, Maryland, New Jersey, Pennsylvania, Puerto Rico, Virgin Islands, Virginia, West Virginia |
| Midwest | Illinois, Indiana, Michigan, Minnesota, Ohio, Wisconsin |
| Mountain Plains | Colorado, Iowa, Kansas, Missouri, Montana, Nebraska, North Dakota, South Dakota, Utah, Wyoming |
| Northeast | Connecticut, Maine, Massachusetts, New Hampshire, New York, Rhode Island, Vermont |
| Southeast | Alabama, Florida, Georgia, Kentucky, Mississippi, North Carolina, South Carolina, Tennessee |
| Southwest | Arkansas, Louisiana, New Mexico, Oklahoma, Texas |
| Western | Alaska, American Samoa, Arizona, California, Guam, Hawaii, Idaho, Northern Mariana Islands, Nevada, Oregon, Washington |

Some of the PSUs that were selected were found to be geographically large. Therefore, in nine PSUs that contained more than five counties, a subset of the counties was selected.

### *Selection of SSUs*

The second stage of selection involved the formation and selection of SSUs. The SSUs consisted of Census Block Groups (BGs), or multiple contiguous BGs if the BG was expected to contain fewer than 50 survey-eligible households.

The MOS for selecting the SSUs was constructed in the same way as the composite MOS for PSUs. However, it was derived using 5-year ACS data that were available for BGs. The 400 SSUs were selected with probability proportionate to the MOS from a list of SSUs sorted by county (relevant only in multi-county PSUs). Address-based sampling (ABS), a methodology in which addresses are sampled from the U.S. Postal Service (USPS) Delivery Sequence File (DSF), was applied in most SSUs; however, as described in Section 3.3.1 in Mathematica's Design Report, "14 SSUs either contained no ABS addresses or a large number of ABS addresses that are not useful for locating households (P.O. Boxes, Rural Delivery)." These 14 SSUs were identified as needing traditional listing procedures. For the 14 SSUs, an average of four Census Blocks were selected for field-listing using probability proportionate to size.

### *Selection of Addresses*

The third stage of selection involved the creation of a sampling frame of addresses, stratification, and selection of addresses that serve as the screening sample for the ultimate selection of the households in the four target groups. The sampling frame of addresses within selected SSUs was created from different sources, including lists of addresses from the USPS DSF (referred to as "ABS" for address-based sampling), traditional listing of addresses (field listed), and a list of addresses for households receiving SNAP benefits in February 2012 from state agencies (SNAP lists). SNAP lists for sampled PSUs were received from 22 of the 27 states that had sampled PSUs in time for sampling purposes. There were three combinations of address sources that constituted the sampling frames within SSUs:

- ABS and SNAP listings (315 SSUs);
- ABS only (71 SSUs), and
- Field listed only (14 SSUs).

In SSUs where SNAP listings existed, SNAP addresses were matched to the ABS list to stratify the addresses into those on the SNAP list and those not on the SNAP list. Probabilistic matching methods were utilized to compare the SNAP list to the ABS frame. Comparing addresses is a difficult task, and it is likely that some addresses on the SNAP frame were duplicated on the final ABS frame, or that mismatches occurred (more discussion in Section 3.3.2 in Mathematica's Design Report).

In SSUs where SNAP listings did not exist, no stratification occurred. With the required oversampling of SNAP households, selection of SNAP addresses from the SNAP list can greatly reduce the number of addresses to screen. In SSUs where SNAP lists existed, the goal was equal overall probabilities for addresses in the SNAP list stratum across SSUs and PSUs, and equal overall probabilities for addresses in the non-SNAP stratum across SSUs. In SSUs with ABS or field listed only, the sampling rates within SSUs were set with the goal of equal overall probabilities of selection across such SSUs.

In some instances, multiple units existed within a selected address. Section 3.3.5 of the Mathematica Design Report discusses the approach for dealing with multi-unit addresses as follows: "Where a sampled address included only one housing unit, that unit was included in the sample; if it contained more than one unit, one or more units (up to six) were sampled at the address." This approach

effectively retains the goal of equal selection probabilities within target groups for addresses with up to six units.

In other instances, some addresses were drop points in the ABS frame rather than individual units. The post office delivers mail at a drop point for two or more units to a common location. Mathematica's Design Report discusses the approach to handle drop points in Section 3.3.3 as follows:

> Because the sampling frame included drop points, we assigned a measure of size to each address in the frame. The MOS is equal to the number of housing units at the address. MOS is equal to one for single-family residences and for units in multi-unit buildings with individual unit numbers; MOS is greater than one for multi-unit buildings identified as drop points.
>
> Drop points were handled in one of two ways in the sampling frame:
>
> a. Buildings with two or three units and no unit numbers (NUN) – we constructed "dummy units" as instructions for field staff of the form: "NUN TAKE 1st UNIT," "NUN TAKE 2nd UNIT," "NUN TAKE 3rd UNIT." Specific instructions for identifying the 1st, 2nd, and 3rd units were provided in the Training Manual and at training. 201 "dummy units" were released to the field.
>
> Buildings with more than three units – we sampled with MOS equal to the number of units. Thirty-one such multi-unit buildings were sampled and field listed to obtain unit numbers (with an average size of 35 units). Twenty-two of these 31 buildings were selected with certainty, and 8 of these 31 buildings were found during listing to be ineligible (group homes or non-existent addresses).

A reserve sample of addresses was selected at the same time as the main sample. The reserve sample consisted of 70 release groups (called replicates). After 4 months, due to an expected shortfall in Target Groups A and B, a supplemental reserve sample comprising 41 release groups was selected for the non-SNAP component. In the end, among the main sample and reserve samples, 42,143 addresses were selected, and 20,084 were released to the field. Section 3.3.6 of the Mathematica Design Report adds:

> Replicates 71-111 were constructed to have the same properties as the original ABS sample. For the SNAP frame, the probability of selection was based on the selections in replicates 1 through 70 only. For the ABS frame, the probability of selection was based on the selections in replicates 1

through 111. For the latter, we treated all selections as concurrent for purposes of the weights.[3]

Due to uncertainty in the assumptions (e.g., vacancy rates, percentages across the target groups, response rates), the release groups were managed closely throughout the data collection period. Each release group had associated open/closed flags that were assigned by combinations of Target Groups and SSUs and the observed shortfalls. More details are provided in Section 3.4 of the Mathematica Design Report.

A screener questionnaire was administered to selected households. Screener items related to income, household size, and receipt of SNAP were asked so that households could be categorized in the four target groups. If determined to be in an "open" target group, as assigned among the release groups, the household was eligible to participate in the study. If the household was in a closed group, the household was screened out.

Lastly, in mid-October 2012, a sample of the 985 addresses, across all PSUs, that had been initially closed out as nonrespondents were given a second chance for extra attempts. About 14 percent (138 cases) were randomly selected, 89 percent non-SNAP and 11 percent SNAP, and re-released to the field for up to 10 additional contact attempts. The effort resulted in 12 completed final interviews that were added to the 4,814 completed households. In total, 4,826 households completed the FoodAPS-1 survey.

[3] Calculating overall selection probabilities when going back in for a second round of sampling is not straightforward when selections are made with PPS. The probability of a non-certainty address being selected within an SSU (or TSU) in the second round (P2) is dependent on not being selected in the first round (1 - P1), and that depends on the measures of size of those addresses actually selected in the first round. Thus, we made the assumption for weighting that the value of P1 was fixed, as most addresses had a measure of size of 1. This assumption simplifies the overall probability of selection, P = P1 + (1-P1) P2, to $P = (n_1 + n_2)MOS_i/\sum MOS_i$, where $n_1$ and $n_2$ are the number of non-certainty addresses selected within SSU/TSU in the first and second rounds, respectively.

## 1.3 Results from the Sample Design

The above paragraphs provide the most important features of the sample design. There were several complicating factors in the assignment of selection probabilities to account for special circumstances, which include the:

- Subsampling of counties in some PSUs;
- Subsampling of blocks within some SSUs;
- Selecting the dwelling units within large drop points;
- Subsampling of nonrespondents for extra screener attempts; and
- Assignment of open/closed designations, and release groups.

Further details about the special situations related to the sample design can be found in the unpublished Mathematica Design Report. The latter two factors were attempts to address shortfalls in the sample. The first four factors above can be easily handled; however, it is likely that the fifth factor has the most potential of affecting the precision of the estimates. Table 1-3 provides the resulting actual sample sizes. The deviations in actual sample sizes from the planned sample sizes shown in Table 1-3, such as 346 for Target Group A when targeting 800 households, is a result of the challenges of conducting surveys for the subgroups of interest in FoodAPS even after extra efforts were attempted.

**Table 1-3. Planned and actual household sample sizes by target group**

| Target group | Planned | | Actual | |
|---|---|---|---|---|
| | Sample size | Percent (%) | Sample size | Percent (%) |
| A: Non-SNAP households with income less than the poverty guideline | 800 | 16.0 | 346 | 7.2 |
| B: Non-SNAP households with income greater than or equal to 100 percent and less than 185 percent of the poverty guideline | 1,200 | 24.0 | 851 | 17.6 |
| C: Non-SNAP households with income greater than or equal to 185 percent of the poverty guideline | 1,500 | 30.0 | 2,048 | 42.4 |
| D: SNAP households | 1,500 | 30.0 | 1,581 | 32.8 |
| Total | 5,000 | 100.0 | 4,826 | 100.0 |

The FoodAPS-1 sample design results discussed in this report can help to provide information leading to a more efficient sample design in the next main survey. Key aspects to improving the design are:

- Limiting the impact of sampling decisions, such as the administration of release groups, on the variation in the sampling rates and the sampling weights;
- Understanding the amount of misclassification (e.g., screening classification versus final classification) and its impact on the precision of estimates;
- Evaluating the impact of clustering the dwelling unit sample within selected areas on precision of estimates;
- Determining the numbers of PSUs and SSUs to select, and assessing the impact of increasing number of degrees of freedom on analyses; and
- Investigating the impact of stratification.

Attempts to gauge the quality of the undercoverage of the lists were described in Section 3.6 of the Mathematica Design Report, as follows:

> The accuracy of the frame was assessed during the study by the half-open interval frame-linking procedure (Kish, 1965). By checking for units between a sampled address and the next address on the frame, addresses not on the frame are given a chance of being selected for the sample. The procedure thus increases coverage within areas that have some addresses on the sampling frame. Every sample address was assigned "adjacent address information" to be verified by field staff. Adjacent addresses were identified from the full sample frame prior to sampling. We sorted the frame by USPS delivery point barcode (DPBC) and selected the next address as the adjacent address. If the "next" address was not in the same block (9-digit ZIP code), the adjacent address was identified as the prior address. If there were no addresses on the same block, the adjacent address was identified as "None."[4] We identified "adjacent address information" for every sample address: 93.7 percent of sample addresses were assigned adjacent address information containing an address or number of units requiring verification; 6.3 percent of sample addresses were assigned "None", indicating that field staff needed to verify the lack of another residential address on the same block.

[4] The DPBC enables automated mail sorting that corresponds to the walk sequence of letter carriers. The last 4 digits of the 9-digit ZIP code identify a segment or one side of a street: http://faq.usps.com/eCustomer/iq/usps/request.do?create=kb%3AUSPSFAQ&view()=c%5bc_usps0901%5d.

More details are given in the Mathematica Design Report. The results of the investigation were provided as follows:

> Overall, the findings of the adjacent address check did not identify a substantial number of units absent from the sampling frame (most errors in the frame identified units that didn't exist) so [an] additional sample was not selected from the adjacent address verification results.

An important part of the sample design when ABS lists are used is to conduct quality control on the lists received from the various sources, as was done here with the half-open interval method. In general, an address list enhancement should be done to reduce the coverage bias. Other aspects, such as investigating the choice of PSUs and SSUs, the measures of size used for selecting PSUs and SSUs to focus the sample on the subgroups of interest, or planning the sample for WIC as a key sampling domain, will be addressed in the sampling plan for the next main study.

## 1.4 Precision of Four Key Survey Estimates from the FoodAPS-1 Survey

The FoodAPS-1 complex sample design was investigated as to the impact on the precision of the sample estimates. Estimates and sampling error measures, including standard errors (SEs), coefficients of variation (CV), design effects, and effective sample sizes, were computed for average expenditures on FAH events, on FAFH events, the average number of free events per household, and the proportion food insecure, overall, by target group (Table 1-4), by WIC household classification (Table 1-5), by metro/nonmetro status (Table 1-6) and by rural/non-rural status (Table 1-7). The sampling error measures were computed using the stratified jackknife replicate weights and are described in Appendix A.

Among Tables 1-4 through 1-7, the SEs for the marginals (full sample) were smaller, sometimes much smaller, than the SEs for subgroups. This is mostly due to the larger effective sample size in the full sample.

A target CV is arguably 5 percent, while warnings (caution) are given by some government agencies (e.g., National Center for Education Statistics) for estimates with CVs from 30 to 50 percent, and even suppress estimates with CVs greater than 50 percent. As seen in Tables 1-4 through 1-7, all CVs are below 20 percent. The national estimates have CVs lower than 5 percent, while the CVs for

subgroups are higher (up to 18.2 percent). The indicators of precision suggest that some improvements in the sample design may be helpful. This report will help to explore reasons for the higher CVs and SEs, and considerations for ways to reduce them.

Table 1-4. Estimates and sampling error measures by outcome of interest and target groups

| Outcome of interest | Estimate[1] | SE | DEFF | CV | Sample size | Effective sample size |
|---|---|---|---|---|---|---|
| **Total FAH per week** | | | | | | |
| Group A | $67.51 | 5.61 | 2.262 | 8.3 | 330 | 146 |
| Group B | $72.55 | 3.25 | 1.723 | 4.5 | 829 | 481 |
| Group C | $116.67 | 3.89 | 2.447 | 3.3 | 2,011 | 822 |
| Group D | $94.14 | 4.03 | 2.208 | 4.3 | 1,529 | 692 |
| Marginal | $105.72 | 2.83 | 3.342 | 2.7 | 4,699 | 1,406 |
| **Total FAFH per week** | | | | | | |
| Group A | $30.43 | 5.09 | 3.335 | 16.7 | 328 | 98 |
| Group B | $34.37 | 2.96 | 2.766 | 8.6 | 825 | 298 |
| Group C | $67.55 | 2.00 | 1.350 | 3.0 | 1,975 | 1,463 |
| Group D | $30.99 | 2.03 | 1.980 | 6.6 | 1,532 | 774 |
| marginal | $56.52 | 1.45 | 1.896 | 2.6 | 4,660 | 2,458 |
| **Total Free Events** | | | | | | |
| Group A | 2.47 | 0.35 | 2.283 | 14.0 | 339 | 149 |
| Group B | 2.61 | 0.22 | 1.949 | 8.3 | 839 | 431 |
| Group C | 2.95 | 0.17 | 3.03 | 5.7 | 2,034 | 671 |
| Group D | 3.96 | 0.17 | 1.402 | 4.4 | 1,527 | 1,089 |
| marginal | 3.02 | 0.13 | 3.85 | 4.3 | 4,739 | 1,231 |
| **Food Insecurity** | | | | | | |
| Group A | 0.42 | 0.04 | 1.834 | 8.5 | 346 | 189 |
| Group B | 0.24 | 0.02 | 1.291 | 6.9 | 851 | 659 |
| Group C | 0.07 | 0.01 | 1.577 | 10.3 | 2,048 | 1,299 |
| Group D | 0.45 | 0.02 | 2.558 | 4.4 | 1,581 | 618 |
| marginal | 0.16 | 0.01 | 1.269 | 3.7 | 4,826 | 3,803 |

[1] The estimates are means, except for food insecurity (proportions).

Table 1-5. Estimates and sampling error measures by outcome of interest and WIC household classification

| Outcome of interest | Estimate[1] | Standard error | DEFF | CV | Sample size | Effective sample size |
|---|---|---|---|---|---|---|
| **Total FAH per week** | | | | | | |
| non-WIC | $147.95 | 11.09 | 4.076 | 7.5 | 535 | 131 |
| WIC | $116.93 | 8.67 | 2.829 | 7.4 | 447 | 158 |
| marginal | $139.38 | 8.89 | 5.128 | 6.4 | 982 | 191 |
| **Total FAFH per week** | | | | | | |
| non-WIC | $65.42 | 3.49 | 0.87 | 5.3 | 523 | 601 |
| WIC | $55.59 | 5.27 | 2.56 | 9.5 | 442 | 173 |
| marginal | $62.67 | 3.47 | 1.748 | 5.5 | 965 | 552 |
| **Total Free Events** | | | | | | |
| non-WIC | 4.50 | 0.40 | 2.454 | 8.9 | 541 | 220 |
| WIC | 4.96 | 0.41 | 1.911 | 8.2 | 456 | 239 |
| marginal | 4.63 | 0.33 | 2.949 | 7.1 | 997 | 338 |
| **Food Insecurity** | | | | | | |
| non-WIC | 0.15 | 0.03 | 3.058 | 18.2 | 546 | 179 |
| WIC | 0.30 | 0.04 | 4.083 | 14.4 | 461 | 113 |
| marginal | 0.19 | 0.02 | 2.943 | 11.2 | 1,007 | 342 |

[1] The estimates are means, except for food insecurity (proportions).

Table 1-6. Estimates and sampling error measures by outcome of interest and metro/non-metro classification

| Outcome of interest | Estimate[1] | Standard error | DEFF | CV | Sample size | Effective sample size |
|---|---|---|---|---|---|---|
| **Total FAH per week** | | | | | | |
| Metro | $107.86 | 3.38 | 4.132 | 3.1 | 4,286 | 1,037 |
| non-Metro | $91.85 | 8.26 | 3.843 | 9.0 | 413 | 107 |
| marginal | $105.2 | 2.83 | 3.342 | 2.7 | 4,699 | 1,406 |
| **Total FAFH per week** | | | | | | |
| Metro | $59.56 | 1.67 | 2.141 | 2.8 | 4,248 | 1,984 |
| non-Metro | $37.05 | 3.92 | 2.524 | 10.6 | 412 | 163 |
| marginal | $56.52 | 1.45 | 1.896 | 2.6 | 4,660 | 2,458 |
| **Total Free Events** | | | | | | |
| Metro | 3.09 | 0.13 | 3.601 | 4.3 | 4,331 | 1,203 |
| non-Metro | 2.57 | 0.41 | 3.597 | 16.1 | 408 | 113 |
| marginal | 3.02 | 0.13 | 3.85 | 4.3 | 4,739 | 1,231 |
| **Food Insecurity** | | | | | | |
| Metro | 0.16 | 0.01 | 1.302 | 3.9 | 4,400 | 3,378 |
| non-Metro | 0.14 | 0.02 | 1.518 | 14.8 | 426 | 281 |
| marginal | 0.16 | 0.01 | 1.269 | 3.7 | 4,826 | 3,803 |

[1] The estimates are means, except for food insecurity (proportions).

Table 1-7. Estimates and sampling error measures by outcome of interest and rural/non-rural classification

| Outcome of interest | Estimate[1] | Standard error | DEFF | CV | Sample size | Effective sample size |
|---|---|---|---|---|---|---|
| **Total FAH per week** | | | | | | |
| non-Rural | $104.29 | 3.09 | 2.805 | 3.0 | 3,420 | 1,219 |
| Rural | $108.53 | 5.48 | 3.619 | 5.1 | 1,279 | 353 |
| marginal | $105.72 | 2.83 | 3.342 | 2.7 | 4,699 | 1,406 |
| **Total FAFH per week** | | | | | | |
| non-Rural | $59.68 | 1.93 | 2.172 | 3.2 | 3,395 | 1,563 |
| Rural | $50.328 | 2.69 | 2.414 | 5.3 | 1,265 | 524 |
| marginal | $56.52 | 1.45 | 1.896 | 2.6 | 4,660 | 2,458 |
| **Total Free Events** | | | | | | |
| non-Rural | 3.04 | 0.15 | 3.527 | 4.9 | 3,452 | 979 |
| Rural | 2.98 | 0.25 | 4.333 | 8.4 | 1,287 | 297 |
| marginal | 3.02 | 0.13 | 3.85 | 4.3 | 4,739 | 1,231 |
| **Food Insecurity** | | | | | | |
| non-Rural | 0.18 | 0.01 | 1.625 | 4.6 | 3,515 | 2,163 |
| Rural | 0.13 | 0.01 | 2.155 | 10.7 | 1,311 | 608 |
| marginal | 0.16 | 0.01 | 1.269 | 3.7 | 4,826 | 3,803 |

[1] The estimates are means, except for food insecurity (proportions).

Among target groups, Target Group A has the highest CVs ranging from 8.3 to 16.7 percent across the outcome variables. While there is interest within target groups by WIC, non-metro, and rural classifications, the sample sizes and degrees of freedom become small, and, therefore, the classifications are studied without regard to target group. Because of the large sample sizes, the results for metro and non-rural classifications align closely with the full sample results, and, therefore, we discuss only non-metro and rural results.

Among WIC households, as shown in Table 1-5, food insecurity has the highest CV (14.4%) and FAH has the lowest (7.4%). The sample sizes for the WIC classification of WIC/nonWIC are smaller than for other groups, because the questionnaire items from which the estimates were derived were only asked of households with someone in HH AGE = 14 - 49 and SEX = 2 and ANYPREGNANT = 1, or if someone in the household was under age 5. Among non-metro areas, as shown in Table 1-6, the estimate for free items has the highest CV (16.1%) and FAH has the lowest (9.0%). Among rural areas, as shown in Table 1-7, food insecurity has the highest CV (10.7%) and FAH has the lowest (5.1%).

The impact of the sample design on the above measures of precision can be studied by computing the design effect $(DEFF)$. The $DEFF$ is a useful quantity to examine when comparing alternative designs. The $DEFF$ is computed as:

$$DEFF = \frac{Estimated\ variance\ under\ complex\ design}{Estimated\ variance\ under\ SRS}$$

Since the FoodAPS design consists of a multistage cluster sample, the $SE$ is typically larger than under $SRS$. One interpretation of $DEFF$ says that if $DEFF = 2$, the sample size needs to be doubled in order to achieve the same precision as from an $SRS$. Another interpretation is that if the resulting sample size from the complex sample is 5,000 respondents, then with a $DEFF = 2$, the effective sample size is 2,500.

Overall, the $DEFF$s range from 1.3 for food insecurity to 3.8 for free items. DEFFs very much depends on the requirements for the sample design. As given in the OMB Part B document, based on assumptions on design effects from clustering and differential sampling rates, a broad range of DEFFs was expected for overall estimates (2.99 to 8.93) for national estimates. Our impression is that DEFF estimates are a bit noisy, but look reasonable, especially when compared to expectations. The effective sample size ranges from 1,231 for free items to 3,803 for food insecurity. Differences between resulting values of $DEFFs$ can be the result of the following:

1. Sample size;
2. Differential sampling rates, and variation in the sample weights (investigated in Section 2);
3. Clustering (Section 3); and
4. Stratification (Section 4).

There is no pattern in the $DEFFs$ across target groups, with the exception that the $DEFFs$ for Target Group A are slightly higher than the other groups, ranging from 1.8 for food insecurity and 3.3 for FAFH. Target Group A has the lowest effective sample sizes, with the lowest being 98 for FAH, while Target Group C has the highest effective sample sizes, with the highest being 1,463 for FAFH.

Among WIC households, as shown in Table 1-5, the $DEFFs$ range from 1.9 for free items to 4.1 for food insecurity. The effective sample size ranges from 113 for food insecurity to 239 for free items. Among non-metro areas, as shown in Table 1-6, the $DEFFs$ range from 1.5 for food insecurity to

3.8 for FAH. The effective sample size ranges from 107 for FAH to 281 for food insecurity. Among rural areas, as shown in Table 1-7, the *DEFFs* range from 2.1 for food insecurity to 4.3 for free items. The effective sample size ranges from 297 for free items to 608 for food insecurity.

In terms of the effective sample sizes, at the national level, they exceeded the upper bound on the range of expected effective sample size for two of the four outcome measures. For Target Group C, while the actual sample size surpassed the targeted sample size, the upper bound of the effective sample size was exceeded by two of the outcome measures. However, for one outcome measure, the effective sample size was closer to the lower bound. For SNAP (Target Group D), while the actual sample size was about the same as planned, the effective sample size was closer to the lower bound for two (and marginally for three) of the outcome measures. It is for the smaller subgroups, such as the Target Groups A and B, where effective sample sizes were smaller than desired.

Typically DEFFs for subgroups should be less than DEFFs for national estimates. This is because less clustering and less variation in sampling weights are expected for subgroups[5]. However, in FoodAPS, the DEFFs for subgroups are roughly at about the same level as for the national estimates. The indicators of precision (SEs, DEFF, CV, effective sample sizes) are at reasonable levels for national estimates, but there are indications that there may be ways to improve the sample design for subgroups.

We investigated the impact of the FoodAPS-1 sample design on key comparisons of interest.. Having clusters that include participating households from both groups being compared reduces the associated variance of the estimated difference due to the covariance of the two estimates introduced by the cluster sampling. That is, for example, because each PSU and many SSUs likely had participants from both Target Groups A and D, the clusters act as a controlling factor, and the variance of the difference is lower than if the two groups came from two independent samples.[6] We define a *"DEFF"* to be the ratio of the estimated variance under the FoodAPS-1 complex design, taking into account the covariance between A and D, to the variance estimate of the difference under the assumption of SRS and the samples for A and D are independent. The results in Table 1-8 show that the *DEFFs* range from 1.68 for total free events to 2.82 for FAFH expenditures.

[5] This expectation is illustrated in the FoodAPS-1 OMB Part B document.

[6] However, a design that aims to arrive at precise estimates for only A or D would require less of a sample than if the design were to aim for precise estimates for comparisons between A and D.

Table 1-8. Estimated difference between Target Groups D and A, standard error, and design effect by outcome

| Difference: Target groups A and D | Estimate | SE | DEFF |
|---|---|---|---|
| Total Food At Home | 26.64 | 6.756 | 2.15 |
| Total Food Away from Home | 0.56 | 5.27 | 2.82 |
| Total Free Events | 1.48 | 0.353 | 1.68 |
| Food Security | 0.03 | 0.041 | 1.95 |

Similarly, aligning with the FoodAPS-1 study objectives, comparisons also were made between Target Groups A, B, D with C in Table 1-9 and Target Groups A, B, C with D in Table 1-10. The $DEFFs$ were greater than 1 in all cases as expected. The magnitude of the $DEFFs$ for the comparisons are in general slightly lower than the $DEFFs$ computed in Tables 1-4 through 1-7 for groups by themselves (without the comparisons) due to the covariances.

Table 1-9. Estimated difference between Target Group C versus Target Groups A, B, and D, standard error and design effect by outcome

| Difference: Target groups C-ABD | Estimate | SE | DEFF |
|---|---|---|---|
| Total Food At Home | 35.58 | 4.269 | 2.01 |
| Total Food Away from Home | 35.26 | 2.38 | 1.41 |
| Total Free Events | -0.21 | 0.222 | 2.62 |
| Food Security | -0.29 | 0.017 | 2.60 |

Table 1-10. Estimated difference between Target Group D versus A, B, and C, standard error and design effect by outcome

| Difference: Target groups D-ABC | Estimate | SE | DEFF |
|---|---|---|---|
| Total Food At Home | -13.36 | 4.855 | 2.16 |
| Total Food Away from Home | -29.58 | 2.018 | 1.07 |
| Total Free Events | 1.08 | 0.194 | 1.38 |
| Food Security | 0.34 | 0.022 | 2.65 |

The contractor provided broad ranges in the Office of Management and Budget (OMB) Part B document of the expected precision. In general, the resulting measures of precision look reasonable at the national level (i.e., for the total sample). For example, as discussed in the OMB Part B document, for the amount spent on food at home (FAH), the projected 95 percent confidence intervals (half-widths) for total weekly food expenditures were expected to range at the national level from $5.11 to $8.83. For comparison with the actual results, multiply the SEs in Table 1-4 by 2 to compare to the expected half-width confidence interval values. For FAH, the half-width is about $5.66 (2 multiplied by 2.83).

For the purpose of comparing two groups, minimum detectable differences (MDDs) were estimated with 80 percent power and 95 percent confidence during the design phase, which took into account assumptions about the impact of the complex design. In general, the resulting measures of precision for the comparisons look reasonable. For example, when comparing FAH expenditures between the largest groups (Target Group C with Target Groups A, B, D), the resulting detectable difference is approximately $8.54 (given in Table 1-9 by multiplying the SE by 2), which is actually lower than the lower bound on the expected MDDs, which ranged from $10.49 to $15.64 depending on the design effect assumptions. For the smaller subgroups, such as the Target Groups A and B where effective sample sizes were smaller than desired for FAH and FAFH expenditures, when making comparisons with Target Group D, the large sample size in Target Group D helped the resulting actual MDDs to fall into the broad range of expected MDDs.

The results from Tables 1-4 through 1-10 led to an investigation into the causes of the magnitudes of the $DEFFs$ and the resulting decreases in the effective sample sizes for subgroups, which may prove beneficial in developing a sample design that results in higher effective sample sizes for key domains of interest and key comparisons of interest.

The total variance of an estimate can be decomposed into components of variance (such as the impact due to differential sampling rates [or weights], clustering, and stratification) so that reasons for larger unexpected variation can be determined. In general, the overall $DEFF$ is sometimes expressed as the product of two components: $DEFF_{UEW}$, which is due to differential sampling rates (or unequal weighting), and $DEFF_{CLU}$, which is due to clustering. That is, $DEFF = DEFF_{UEW} \times DEFF_{CLU}$. This multiplicative model, given by Kish (1995), is a common model for the handling of ways to extract the differential weighting impact from the clustering impact. This report investigates the components of variance toward recommendations for improving the sample design for the next main survey of FoodAPS. In the following sections, the impact of the sample design on the total variance is examined through parsing out the main contributing factors: differential weights (Chapter 2), clustering (Chapter 3), and stratification (Chapter 4). We conclude with further discussion and recommendations in Chapter 5.

# Design Effect Due to Unequal Weights 2

When planning a sample, the $DEFF$ due to differential sampling rates, as given in Kish (1965), can be expressed as $DEFF_{UEW} = (\frac{\sum W_h}{k_h})(\sum W_h\, k_h)$, where, $W_h = N_h/N$, $N$= total population size, $N_h$= population size for stratum $h$, and $k_h$ = sampling rate within stratum $h$. Using this expression and the sample and population proportions given in Table 1-1 (from which sampling rates are inferred), the planned $DEFF_{UEW}$ due to differential sampling rates was 1.62 for FoodAPS-1. However, the weight adjustments are another source of variation beyond the differential sampling rates, and therefore the expression for $DEFF_{UEW}$ is most usefully expressed as $1 + CV^2$, as given in Kish (1992), where the $CV$ of the weights is the standard deviation of the weights relative to the average weight.

To systematically show the impacts of the sample design, sampling-related decisions to address shortfalls in the sample yield, and weight adjustments, the $DEFF_{UEW}$ were computed by Westat for the base weights and most steps in the weight process to investigate their impact. Table 2-1 provides estimates of the $DEFF_{UEW}$ at each stage of weights for the sample groups of interest (i.e., the study's four target groups, WIC households, and households classified by metro and rural location). Additionally, to examine the effect of misclassification into target group at the screener level, $DEFF_{UEW}$ were also computed for the target group that was assigned during the screener. Results shown in Table 2-1 will be discussed in detail throughout this chapter.

Table 2-1. Design effect at each stage of weighting for various analysis domains

| Analysis domain | Screener base weight | Screener nonresponse adjusted weight | Screener deselection weight | Extended nonresponse adjusted weight | Final raked weight |
|---|---|---|---|---|---|
| Overall | 1.59 | 1.60 | 2.12 | 2.60 | 2.67 |
| **Final Target Group (after extended survey)** | | | | | |
| Group A | 1.53 | 1.48 | 1.61 | 1.81 | 2.30 |
| Group B | 1.41 | 1.40 | 1.65 | 2.11 | 2.39 |
| Group C | 1.47 | 1.46 | 1.74 | 2.07 | 2.01 |
| Group D | 1.77 | 1.85 | 2.45 | 2.78 | 2.47 |
| **Interim Target Group (as defined by screener)** | | | | | |
| Group A | 1.57 | 1.56 | 1.56 | 1.75 | 2.34 |
| Group B | 1.43 | 1.43 | 1.43 | 1.91 | 2.02 |
| Group C | 1.46 | 1.43 | 1.37 | 1.57 | 1.50 |
| Group D | 1.82 | 1.92 | 2.55 | 2.73 | 2.57 |
| **WICHH** | | | | | |
| non-WIC | 1.49 | 1.59 | 2.16 | 2.37 | 2.40 |
| WIC | 1.53 | 1.60 | 2.02 | 2.73 | 2.37 |
| **Metro/nonmetro** | | | | | |
| Metro | 1.51 | 1.53 | 2.03 | 2.47 | 2.58 |
| non-Metro | 1.60 | 1.66 | 2.25 | 2.68 | 2.70 |
| **Rural** | | | | | |
| non-Rural | 1.46 | 1.49 | 1.89 | 2.34 | 2.50 |
| Rural | 1.70 | 1.72 | 2.37 | 2.34 | 2.78 |

### *Base Weights*

The base weights are computed as the inverse of the overall probability of selection of addresses released to the field. The impacts due to deselection and misclassification are not reflected at this first step in the weighting.

Beyond the oversampling of addresses on SNAP lists, the base weights may vary due to the various sampling activities summarized in Section 1.3 that led to the addresses selected for the screener questionnaire. It is not clear why excess weight variation would result, because ways exist to limit the amount of weight variation when handling drop points, and when reducing costs by subsampling counties within some PSUs and subsampling blocks within some SSUs. In addition, sampling-related decisions to address shortfalls in sample yield during the data collection period may cause a potential increase to the variation in the base weights (even when misclassification and deselection is not yet contributing to the $DEFF$ at this step). These attempts include the SSU- and target group-specific releases of replicate samples, and the nonresponse followup adjustment associated with the two-phase sampling.

As is shown in Table 2-1, the $DEFF_{UEW}$ for the base weights overall is 1.59. This is not yet comparable to the originally planned design effect of 1.62 because the base weight does not account for the deselection for target group sampling rates after the screener responses are known. For the four outcomes of interest presented in the table (food insecurity, total amount spent on food consumed at home events, total spent on food away from home events, and total number of free events), the $DEFF_{UEW}$ ranged from 1.41 to 1.77. The biggest differences in $DEFF_{UEW}$ occur across target group with Target Groups B and C having the smallest $DEFFs$ and Target Group D having the largest. Generally, and not surprisingly, the $DEFFs$ for the screener target groups are similar to the $DEFFs$ for the main study target groups because the deselection rate is not yet accounted for in the base weights step.

The sampling plan for the next main survey can use the information above to ensure that weight variation is reduced or eliminated in certain sample design features discussed in Sections 1.1 and 1.2, such as protocols related to release groups and other subsampling occurrences.

### *Screener Nonresponse Adjustment*

The screener nonresponse adjusted weights in Table 2-1 account for the weight adjustments for unknown address occupancy status and for nonresponse to the screener. Within cells, the screener base weights of sampled addresses where occupancy status was unknown were adjusted by a factor equal to the inverse of the weighted proportion of cases for which occupation status was determined. Then the weights of screener respondents were adjusted by a factor equal to the inverse of the weighted proportion of occupied households that completed the screener. The weighting cells for the occupancy and screener nonresponse adjustments were defined by Mathematica based on the results of a classification tree analysis. The analysis evaluated the relationship of a set of auxiliary variables to occupancy status and screener response status, respectively. The auxiliary variables included sampling frame information (whether the address came from the SNAP list, ABS list, or field listing and whether the PSU was in a metropolitan area) and area-level variables related to vacancy rates, SNAP participation, poverty status, race/ethnicity, and other demographics.

An increase to the $DEFF_{UEW}$ can be expected after nonresponse adjustments because of the trade-off between the reduction in bias due to nonresponse with an increase to variance in the weights. The more the adjustment factor varies among weighting cells, the higher the likelihood that bias is reduced, provided that the weighting cells are related to the outcome of interest. That being said, the screener nonresponse adjustment had very little impact on the overall $DEFF_{UEW}$. The $DEFFs$ for the subgroups of the outcomes of interest also increased slightly for all outcomes except for target group. Among groups the $DEFF_{UEW}$ decreased after the nonresponse adjustment for Target Groups B and C and increased for Target Groups A and D. This is true for both the screener and main study target group.

### *Post-Screener Deselection*

Initial weights for households selected for the initial interview accounted for cases that were deselected after the screener by using the open/closed sampling flags, which were assigned by target groups and by SSUs to control the sample yield after screener responses were provided. The result of the adjustment is the "main study base weight," which is the product of the screener nonresponse adjusted weight and the inverse of the inclusion probability for the initial interview. As discussed in Appendix D of the FoodAPS-1 User Manual, as part of this step, weights were adjusted to include

80 cases that should have been dropped as a result of the quota group subsampling, but they were nonetheless included among the completed cases.[7]

Screener deselection had a significant impact on the $DEFF_{UEW}$. After screener deselection, the overall $DEFF_{UEW}$ increased from 1.60 to 2.12, an increase of 32 percent. This large increase was true for every grouping in the table. The value of 2.12 is most comparable to the planned $DEFF$ due to differential sampling rates. As mentioned above, using the planned sample sizes, and the population proportions from the Mathematica Design Report, as shown in Table 2-1, the $DEFF$ (due to differential sampling rates) = 1.62, which implies a 62 percent increase to variances on national estimates. The OMB Part B document assumes $DEFF_{UEW}$= 1.5 overall, and lower for subgroups, such as 1.07 among SNAP households, and among non-SNAP lower than the 185 percent poverty guideline.

The largest increases were in the rural and non-metro subgroups, increasing by 38 and 35 percent, respectively. The smallest increase was in main study Target Group A, with only a 9 percent increase. It is interesting that when looking at the interim (or screener) target group classification, there was very little change in $DEFF_{UEW}$ as seen in the "after the screener deselection" column for any subgroup except for Target Group D. That is, disregarding Target Group D, if the initial target group was the true target group, which assumes that there were not any misclassification errors between the screener and final target group assignments, the deselection would have had a very minimal impact on the $DEFF_{UEW}$. For Target Group D for the initial target group, the $DEFF_{UEW}$ increased by 33 percent due to misclassification between the SNAP list designation and the screener designation.

### *Main Study Nonresponse Adjustment*

The weight adjustment for nonresponse to the main study (initial interview, diary, final interview) was conducted within 36 weighting cells provided by Mathematica. Mathematica defined the cells based on a classification tree analysis of the relationship between the main study response status and several auxiliary variables. The auxiliary variables included interviewer observations on age, gender,

[7] These 80 residential units were eligible for the survey in all respects except the quota group subsampling, which was designed to more efficiently use survey resources by not interviewing all the households in easier-to-locate quota groups. Once the 80 units were erroneously included, there was no reason not to keep them in the sample with sample weights appropriately adjusted.

and race, screener information on SNAP participation and language, sampling frame information on whether the PSU was in a metropolitan area, and area-level variables related to vacancy rates, SNAP participation, poverty status, race/ethnicity, and other demographics. The main study base weights of the final survey respondent households were adjusted by a factor equal to inverse of the weighted proportion of households that completed the survey, among households selected for the main study.

Adjusting for nonresponse for the main study had a large increase on the $DEFF_{UEW}$, though not quite as large of an impact as the screener deselection adjustment. The nonresponse adjustment increased the $DEFF_{UEW}$ from 2.12 to 2.60, a 23 percent increase. The $DEFF_{UEW}$ increased in every subgroup of the outcomes of interest except for rural households, which had a very minor decrease in $DEFF_{UEW}$. The largest increase in $DEFF_{UEW}$ was in the WIC households and also Target Group B for the main study, with increases of 35 and 33 percent, respectively.

The large increase in $DEFF_{UEW}$ was likely due to the large nonresponse adjustment factors in some of the adjustment cells. In one extreme case, the nonresponse adjustment factor was 9.6. In contrast, the largest adjustment factor for the screener nonresponse adjustment step, which had a very minor impact on the $DEFF_{UEW}$, was only 2.6. Large adjustment factors occur within adjustment cells with low response rates. Collapsing of cells in this type of scenario is often utilized to avoid large adjustment factors that lead to large weight variations. However, collapsing cells reduces the homogeneity of the adjustment cells and reduces the amount of potential bias reduction, so there is a trade-off to be considered.

Among respondents, misclassification is an important cause of weight variation. Further discussion on misclassification is provided after discussing the final weights.

### *Final Weight*

The final weights for FoodAPS-1 resulted from a sequence of adjustments that included a raking adjustment, followed by a weight trimming procedure and a final raking. Weights were calibrated to population control totals for race/ethnicity of respondent, income, receipt of SNAP, household size, number of children in the household, and presence of a member age 60 or older. A weight trimming adjustment was performed within sampling domains, where initial raked weights above a threshold were trimmed down to the threshold, and the trimmed portion was redistributed to the other

weights in the sampling domain. Lastly, final weights for analysis were computed by re-raking the trimmed weights to the population control totals.

The impact of the calibration procedure is similar to the impact from stratification. The aim of the calibration is to use variables in an iterative poststratification process that related to the survey outcomes to reduce the variances of resulting estimates. In doing so, the adjustment may cause some increase to the variation in the weights. The impact of the weight trimming is to reduce the variation in the weights, and to protect from large weights dominating survey estimates, at the expense of a small increase in bias.

The overall impact on the design effect for the raking/trimming/raking steps that resulted in the final weights was minor. The $DEFF_{UEW}$ increased from 2.60 to 2.67, an increase of only 3 percent. However, the impact on the $DEFF_{UEW}$ varied a lot by subgroup of interest. The variation was most dramatic for target groups. There was a decrease in $DEFF_{UEW}$ of 11 percent for the main study Target Group D and an increase in $DEFF_{UEW}$ of 27 percent for Target Group A. Similar patterns were seen for both screener and main study target groups. Other outcomes had more modest changes in $DEFF_{UEW}$ as a result of raking and trimming except for rural households, in which the $DEFF_{UEW}$ increased by 19 percent.

Table 2-2 provides a summary of the weights adjustments' impact on outcome statistics. It is noted that, with the exception of the screener nonresponse adjustment, the weight adjustment steps made an impact on the estimates. For example, for all outcome statistics except total free items, the deselection adjustment made an important correction for the composition of the resulting sample. The extended nonresponse adjustment also made some impact; however, it is unclear that the impact on the potential bias outweighed the impact on the weight variation created by the adjustment. Lastly, with regards to the raking step, with FoodAPS sample size being lower than 5,000 households, the assumption for raking is that the larger survey (source of the control totals) is more accurate. Therefore, the raking adjustment is assumed to reduce the overall mean square error (variance + bias$^2$). The impact on the variation of the weights is assumed to be a result of a positive overall impact on the accuracy of the FoodAPS estimates.

Table 2-2. Estimates of outcome variables across weighting stages

| Outcome of interest | Screener base weight | Screener nonresponse adjusted weight | Screener deselection weight | Extended nonresponse adjusted weight | Final raked weight |
|---|---|---|---|---|---|
| **Total FAH per week** | | | | | |
| Weighted Mean | 50.067 | 50.954 | 56.421 | 59.041 | 56.518 |
| Relative Difference of Mean from Previous Weight Stage (%) | | 1.77 | 10.72 | 4.64 | -4.27 |
| **Total FAFH per week** | | | | | |
| Weighted Mean | 105.304 | 105.522 | 112.694 | 114.118 | 105.724 |
| Relative Difference of Mean from Previous Weight Stage (%) | | 0.21 | 6.80 | 1.26 | -7.36 |
| **Total Free Events** | | | | | |
| Weighted Mean | 3.444 | 3.425 | 3.384 | 3.292 | 3.020 |
| Relative Difference of Mean from Previous Weight Stage (%) | | -0.55 | -1.20 | -2.72 | -8.26 |
| **Food Insecurity** | | | | | |
| Weighted Proportion | 0.235 | 0.233 | 0.187 | 0.174 | 0.159 |
| Relative Difference of Proportion from Previous Weight Stage (%) | | -0.85 | -19.74 | -6.95 | -8.62 |

### *Misclassification*

Recall that the four target groups are defined as follows:

- **Group A.** Non-SNAP households with income less than the poverty guidelines;
- **Group B.** Non-SNAP households with income greater than or equal to 100 percent and less than 185 percent of the poverty guidelines;
- **Group C.** Non-SNAP households with income greater or equal to 185 percent of the poverty guidelines; and
- **Group D.** Households receiving SNAP benefits.

The SNAP list was used to sample SNAP households within sampled SSUs. At the time of the screener, a series of questions was used to determine target group. After the screener, households were subsampled based on their target group designation. During the main survey, a more comprehensive series of questions was used to determine the main study target group. The target group assigned during the main survey was updated based on an up-to-date SNAP list to create the final target group, assigning to SNAP anyone on the SNAP list or who indicated SNAP usage on the main survey. The corrected main study designation of target group should be the most accurate. Ideally, every household designated as a SNAP household on the SNAP list would be categorized as a SNAP household at both the screener and final target group designation (Target Group D), and there would be perfect agreement between the screener and final target group designations. However, in practice, there was misclassification (sometimes referred to as stratum jumpers [Rivest (1999]), and these misclassifications led to increased variation in the final weights.

Tables 2-3 and 2-4 show agreement rates between the SNAP list and the screener and main study designations of target group. Target Group D includes households on SNAP, and all other target groups are not on SNAP. Overall, there is a fairly high agreement between the SNAP list and the screener and corrected main study target group assignments, at 84 and 85 percent, respectively. The SNAP list seems to have better accuracy designating households that are not SNAP households with 86 percent agreement for the screener and 88 percent agreement for the main study. Conversely, when used to identify SNAP households, the SNAP list is only in agreement with the screener target group for 80 percent of households, and for the corrected main study target group designation it is only 77 percent of households. Only 22 of the 27 states in the PSU sample provided SNAP lists, and these tables include data only from those 22 states.

Table 2-3. Screener target group assignment and SNAP list agreement

| Screener target group assignment | SNAP list | Frequency | In-cell agreement | Overall agreement |
|---|---|---|---|---|
| A, B, C | Not SNAP | 2,545 | 86% | 84% |
| A, B, C | SNAP | 428 | | |
| D | Not SNAP | 243 | 80% | |
| D | SNAP | 995 | | |

**Note:** Only 22 of the 27 states in the PSU sample provided SNAP lists, and this table includes data only from those 22 states.

Table 2-4. Main study target group assignment and SNAP list agreement

| Main survey target group assignment | SNAP list | Frequency | In-cell agreement | Overall agreement |
|---|---|---|---|---|
| A, B, C | Not SNAP | 2,468 | 88% | 85% |
| A, B, C | SNAP | 322 | | |
| D | Not SNAP | 320 | 77% | |
| D | SNAP | 1,101 | | |

**Note:** Only 22 of the 27 states in the PSU sample provided SNAP lists, and this table includes data only from those 22 states.

One possible reason for disagreement with the SNAP list designation was the time that had elapsed until the interview occurred. The SNAP lists were provided by state agencies in February 2012 prior to sampling households. Data collection occurred over a series of months, with the last interviews occurring many months (nearly a year) after the creation of the SNAP list. Table 2-5 shows the agreement counts and rates between corrected main study target group and the SNAP list throughout the 10 months of data collection. Agreement varies between 79 and 87 percent over the course of the months, with a slight decrease over time. However, among those identified on the SNAP administrative records, the percentage determined to be on SNAP ranges from 77 percent to 83 percent in the first 3 months, and ranges from 62 percent to 72 percent in the last 3 months. The rates may fluctuate due to small sample sizes, and, therefore, if one were to combine months together, the percentages determined to be on SNAP are 82 percent, 75 percent, and 74 percent for April through June, July through September, and October through January, respectively. From this table it does not appear that the timing of the interview is a large source of misclassification, however there would be some benefit to consideration of a refreshed SNAP list.

Table 2-5. Agreement rates with the SNAP list designation over time

| Main study target group | SNAP list | Apr | May | Jun | Jul | Aug | Sept | Oct | Nov | Dec | Jan |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Not SNAP | Not SNAP | 37 | 229 | 247 | 419 | 485 | 372 | 360 | 215 | 66 | 38 |
| Not SNAP | SNAP | 7 | 47 | 41 | 15 | 48 | 30 | 53 | 58 | 13 | 10 |
| In cell agreement | | 84% | 83% | 86% | 97% | 91% | 93% | 87% | 79% | 84% | 79% |
| SNAP | Not SNAP | 3 | 34 | 39 | 58 | 63 | 45 | 51 | 17 | 6 | 4 |
| SNAP | SNAP | 24 | 220 | 196 | 51 | 147 | 83 | 198 | 132 | 34 | 16 |
| In cell agreement | | 89% | 87% | 83% | 47% | 70% | 65% | 80% | 89% | 85% | 80% |
| Among SNAP list, what percentage was determined to be on SNAP? | | 77% | 82% | 83% | 77% | 75% | 73% | 79% | 69% | 72% | 62% |
| Overall agreement | | 86% | 85% | 85% | 87% | 85% | 86% | 84% | 82% | 84% | 79% |

**Note:** Only 22 of the 27 states in the PSU sample provided SNAP lists, and this table includes data only from those 22 states.

Table 2-6 demonstrates the level of agreement between the target group assigned at the screener and the corrected main study target group designation. Agreement between the two target group assignments is quite low, at 64 percent overall. Agreement is highest with group D (those on the SNAP list) with 84 percent agreement. All other group assignments are quite poor, ranging from 52 to 60 percent agreement between the two target group assignments, with group C having the lowest rates of agreement.

**Table 2-6. Main study target group assignment and screener target group assignment agreement**

| Main study target group assignment | Screener target group assignment | Frequency | In-cell agreement | Overall agreement |
|---|---|---|---|---|
| A | A | 173 | 57% | 64% |
| A | B | 103 | | |
| A | C | 12 | | |
| A | D | 14 | | |
| B | A | 232 | 60% | |
| B | B | 445 | | |
| B | C | 51 | | |
| B | D | 17 | | |
| C | A | 157 | 52% | |
| C | B | 664 | | |
| C | C | 903 | | |
| C | D | 19 | | |
| D | A | 110 | 84% | |
| D | B | 106 | | |
| D | C | 17 | | |
| D | D | 1,188 | | |

**Note:** This table was process for the 22 states with PSU sample that provided SNAP lists.

Incorrect screener target group assignment can have a large impact on weight variation. Table 2-7 shows weight variations within target group assignments overall and within screener group assignments. Within the corrected main study target group assignment, there is a lot of weight variation. The standard deviation of the weights is larger than the mean for every target group. The maximum weight in target group ranges from 7.5 to 11.7 times the mean for that cell.

Looking at screener target group assignment cells within corrected main study target group assignment reduces the variability by quite a bit for some of the cells, especially within screener Target Group C. For example, for main study Target Group D, the maximum weight is 8.1 times the mean and the standard deviation is 21 percent larger than the mean. Looking only at screener Target Group C within main study Target Group D, we see that the maximum weight is only 2.2 times the mean and the standard deviation is nearly half the size of the mean. Table 2-6 shows that

Target Group C has the lowest rates of agreement between the two target group designation, which may explain the findings in Table 2-7.

However, the misclassification does not explain all weight variation within the main study target group cells. For example, consider Target Group D, which has the lowest rates of misclassification between the screener and corrected main study designation, as is shown in Table 2-5. The standard error for screener target group D within corrected main study Target Group D is 22 percent higher than the mean, slightly higher than it is for the corrected main study target group overall. The maximum weight for screener Target Group D within corrected main study Target Group D is 8.3, slightly higher than it is for the corrected main study target group overall. Similar mixed results are found for the various other cells.

An ANOVA was performed on the data presented in Table 2-7 to examine the weight variation within corrected main study target group. A generalized linear model was fit to the equation (household weight = screener target group) within each corrected main study target group. Table 2-8 shows the $R^2$ values for each main study target group model. The $R^2$ values indicate that the weight variation due to misclassification is highest in Target Groups B and C. For example, given the variation in the weights observed within Target Group C, the screener target group designation explains 31 percent of that variation.

Table 2-7. Weight variation within target group assignment

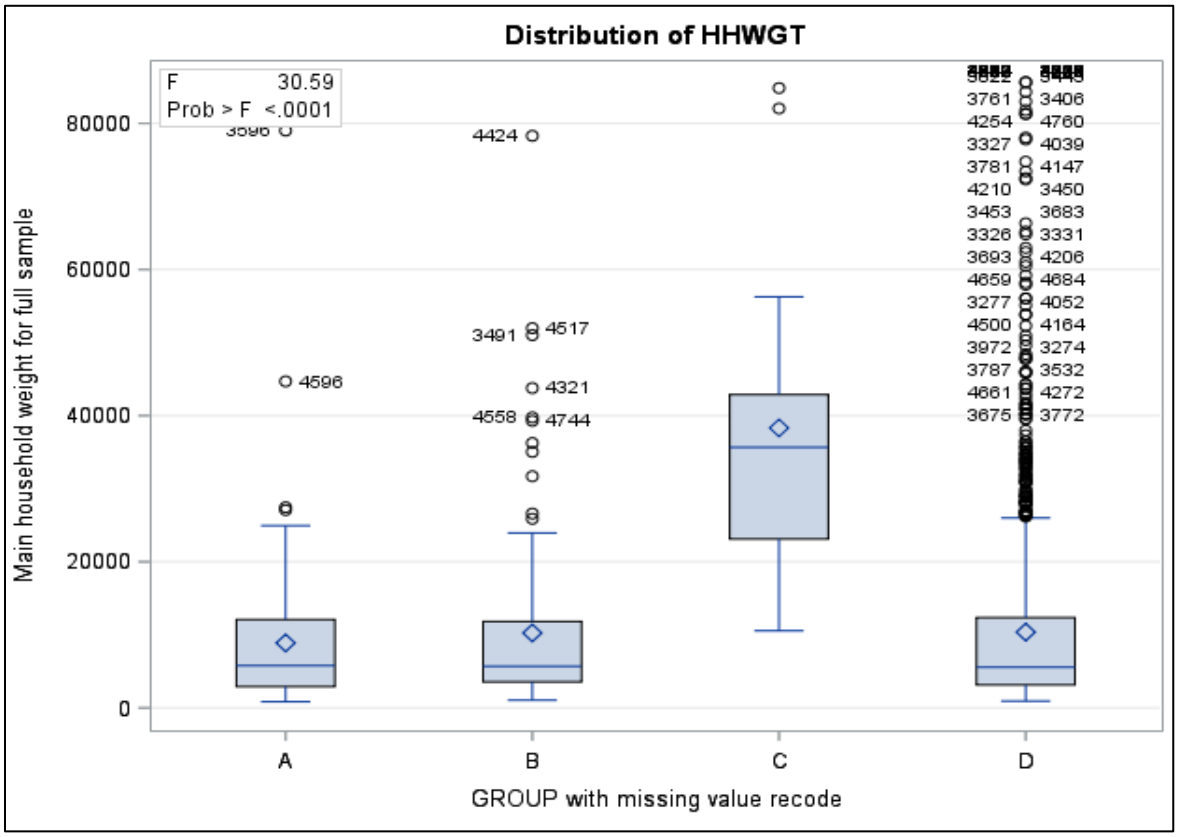
| | N | Mean | Std dev | Min | Max | $DEFF_{UEW}$ | Std dev/mean | Min/mean | Max/mean |
|---|---|---|---|---|---|---|---|---|---|
| **Overall** | | | | | | | | | |
| Target Group A | 346 | 17,176 | 19,549 | 990 | 143,689 | 2.295 | 1.138 | 0.058 | 8.366 |
| Target Group B | 851 | 18,263 | 21,501 | 1,105 | 213,519 | 2.386 | 1.177 | 0.061 | 11.691 |
| Target Group C | 2,048 | 41,150 | 41,287 | 1,019 | 310,558 | 2.007 | 1.003 | 0.025 | 7.547 |
| Target Group D | 1,581 | 10,563 | 12,820 | 836 | 85,627 | 2.473 | 1.214 | 0.079 | 8.107 |
| **Target group A** | | | | | | | | | |
| Screener Group A | 203 | 15,341 | 16,820 | 990 | 143,689 | 2.202 | 1.096 | 0.065 | 9.366 |
| Screener Group B | 115 | 16,473 | 18,850 | 1,245 | 128,890 | 2.309 | 1.144 | 0.076 | 7.824 |
| Screener Group C | 13 | 43,392 | 26,672 | 15,979 | 106,446 | 1.378 | 0.615 | 0.368 | 2.453 |
| Screener Group D | 15 | 24,680 | 32,887 | 1,792 | 87,285 | 2.776 | 1.333 | 0.073 | 3.537 |
| **Target group B** | | | | | | | | | |
| Screener Group A | 258 | 12,394 | 12,622 | 1,105 | 84,961 | 2.037 | 1.018 | 0.089 | 6.855 |
| Screener Group B | 513 | 16,842 | 17,428 | 1,268 | 155,577 | 2.071 | 1.035 | 0.075 | 9.237 |
| Screener Group C | 62 | 56,119 | 39,484 | 4,713 | 213,519 | 1.495 | 0.704 | 0.084 | 3.805 |
| Screener Group D | 18 | 12,503 | 10,896 | 2,513 | 37,217 | 1.759 | 0.871 | 0.201 | 2.977 |
| **Target group C** | | | | | | | | | |
| Screener Group A | 180 | 19,257 | 22,267 | 1,238 | 174,168 | 2.337 | 1.156 | 0.064 | 9.044 |
| Screener Group B | 782 | 16,742 | 15,691 | 1,019 | 205,899 | 1.878 | 0.937 | 0.061 | 12.299 |
| Screener Group C | 1,064 | 63,186 | 44,628 | 4,528 | 310,558 | 1.499 | 0.706 | 0.072 | 4.915 |
| Screener Group D | 22 | 22,100 | 26,167 | 1,829 | 120,841 | 2.402 | 1.184 | 0.083 | 5.468 |
| **Target group D** | | | | | | | | | |
| Screener Group A | 126 | 8,892 | 9,401 | 836 | 79,001 | 2.118 | 1.057 | 0.094 | 8.884 |
| Screener Group B | 128 | 10,253 | 11,847 | 1,052 | 78,300 | 2.335 | 1.155 | 0.103 | 7.637 |
| Screener Group C | 18 | 38,320 | 20,263 | 10,553 | 84,847 | 1.280 | 0.529 | 0.275 | 2.214 |
| Screener Group D | 1,309 | 10,372 | 12,657 | 940 | 85,627 | 2.489 | 1.220 | 0.091 | 8.256 |

Table 2-8. ANOVA results on screener and main study target group assignments

| Final target group | $R^2$ |
|---|---|
| A: Non-SNAP households with income less than the poverty guideline | 0.080 |
| B: Non-SNAP households with income greater than or equal to 100 percent and less than 185 percent of the poverty guideline | 0.253 |
| C: Non-SNAP households with income greater than or equal to 185 percent of the poverty guideline | 0.309 |
| D: SNAP households | 0.055 |

The lower $R^2$ values for Target Group A and D indicate that the between-screener group variation is low among A and among D. For example, 5.5 percent of the variation among the weights for cases classified into corrected main study Target Group D can be explained by the misclassification (difference in screener vs. corrected main study classification). Figure 2-1 is a box-and-whisker plot that illustrates the variation in the weights for corrected main study Target Group D by their screener group designation. Table 2-6 shows that the screener group with the most cases (therefore, most impactful) is D. The figure shows a large number of cases with weights greater than the 75th percentile. One interesting finding is the large number of outliers in the weights for those households categorized as group D in both the screener and corrected main study, which we attempt to explain further below.

Figure 2-1. Box-and-whisker plot of final weights by target group assigned at screener for households in Target Group D, as assigned in main study




**Note:** HHWGT is the final household sample weight.

Further investigation reveals that the mean weight for the SNAP households sampled via ABS is larger than the mean weight for the SNAP households sampled via the SNAP list by a factor of 4.9. Correspondingly, the mean household weight for the SNAP households sampled in states that did not provide lists of SNAP households is larger than the mean weight for SNAP households sampled in states that did provide SNAP lists by a factor of 2.9. For the households that were classified as Target Group D for both the screener and the corrected main study, 91 percent of the weights greater than the 75th percentile were sampled from the ABS frame (the sampling rates differed between the SNAP and ABS frames). To control variation in weights, it is beneficial to capture SNAP households via the SNAP frame as often as possible. One way to aid in this is to emphasize the importance to obtain lists of SNAP households from all states. Additionally, the matching algorithm that compares the SNAP household lists to the ABS frame should be reviewed to ensure the matching algorithm was optimized to ensure adequate removal of SNAP households from the ABS frame prior to sampling. A review of evaluations of the screener items may also be helpful.

# 3 Design Effect Due to Clustering

In the three-stage design for FoodAPS-1, following Hanson, Hurwitz and Madow (1953, Volume 1, Chapter 9, Section 17), the $DEFF$ due to clustering may be expressed approximately as:

$$DEFF_{CLU} = 1 + (\bar{b}_1 - 1)\rho_1 + (\bar{b}_2 - 1)\rho_2 \quad (1)$$

where,

$\bar{b}_1$ = average number of responding households (HHs) per PSU;
$\rho_1$ = intracluster correlation that measures the homogeneity of the characteristic being measured for HHs within the PSUs;
$\bar{b}_2$ = average number of responding HHs per SSU; and
$\rho_2$ = intracluster correlation for HHs within SSUs.

For FoodAPS-1, the intracluster correlation is a measure of similarity among HHs within a cluster. It is helpful to compute the intracluster correlation for designing a more efficient sample. For FoodAPS-1, due to the three-stage design, there are two stages of interest: the intracluster correlation among HHs within PSUs, and the intracluster correlation among HHs within SSUs. In the case of $\rho_1$, it is a measure of how alike HHs are within PSUs. The value provides the proportion of the variation explained by between PSU variance. In the case of $\rho_2$, it measures how alike HHs are within SSUs. The value provides the proportion of the variation (within SSU variance + between SSU variance) explained by between SSU variance. A technical discussion on the computation of $\rho_1$ and $\rho_2$ is provided in Appendix B.

The intracluster correlations for PSUs and SSUs were computed and the results are shown in Table 3-1, overall, and by subgroup for each outcome variable. The values of $\rho_1$ and $\rho_2$ can be negative, partly due to the instability of the estimates of the components of variance. Due to the instability, the estimates of $\rho_1$ and $\rho_2$ may have rather large *SEs* associated with them, especially due to low numbers of degrees of freedom. To explore the sensitivity of the method to extract the differential weighting impact from the clustering impact, there are two different approaches used. For the first approach, as described in Appendix B, for the computation of $\rho_1$, the between PSU variance is divided by the variation among the PSU household average weights. For the computation of $\rho_2$, the between SSU variance is divided by the variation among the average weight for each SSU. For comparison's sake, a second method simply uses equal weights (average) assigned to all

Table 3-1. Intracluster correlations for PSUs and SSUs

| Subgroup | Outcome | Adjustment for weight variation | | Cases assigned average weight | |
|---|---|---|---|---|---|
| | | $\rho_1$ | $\rho_2$ | $\rho_1$ | $\rho_2$ |
| **Overall** | | | | | |
| | FAFH | 0.00 | 0.05 | 0.01 | 0.05 |
| | FAH | 0.01 | 0.10 | 0.00 | 0.07 |
| | Free items | 0.02 | 0.08 | 0.01 | 0.03 |
| | Food insecurity | 0.02 | 0.10 | 0.02 | 0.06 |
| **Target Group** | | | | | |
| A | FAFH | -0.09 | 0.29 | -0.05 | 0.05 |
| B | FAFH | 0.03 | 0.38 | -0.01 | 0.02 |
| C | FAFH | 0.01 | 0.07 | 0.01 | 0.03 |
| D | FAFH | 0.02 | 0.14 | 0.01 | 0.05 |
| A | FAH | 0.13 | 0.38 | 0.06 | 0.20 |
| B | FAH | 0.05 | 0.14 | 0.01 | 0.05 |
| C | FAH | 0.01 | 0.16 | -0.01 | 0.11 |
| D | FAH | 0.02 | 0.12 | 0.01 | 0.06 |
| A | Free items | 0.07 | 0.34 | -0.05 | 0.21 |
| B | Free items | 0.07 | 0.14 | 0.03 | 0.05 |
| C | Free items | 0.04 | 0.18 | 0.01 | 0.08 |
| D | Free items | 0.00 | 0.09 | 0.02 | 0.01 |
| A | Food insecurity | 0.02 | 0.12 | 0.03 | 0.05 |
| B | Food insecurity | -0.01 | 0.18 | -0.01 | 0.12 |
| C | Food insecurity | 0.02 | 0.11 | 0.01 | 0.01 |
| D | Food insecurity | 0.02 | 0.12 | -0.01 | 0.04 |
| **WIC HH Classification** | | | | | |
| Non-WIC | FAFH | -0.03 | 0.33 | -0.03 | 0.07 |
| WIC | FAFH | 0.07 | 0.23 | 0.00 | 0.03 |
| Non-WIC | FAH | 0.13 | 0.55 | 0.00 | 0.16 |
| WIC | FAH | 0.21 | 0.38 | 0.05 | 0.06 |
| Non-WIC | Free items | 0.11 | 0.28 | 0.04 | 0.00 |
| WIC | Free items | 0.02 | 0.30 | 0.00 | 0.12 |
| Non-WIC | Food insecurity | 0.05 | 0.29 | 0.02 | 0.06 |
| WIC | Food insecurity | 0.22 | 0.27 | 0.16 | 0.01 |

Table 3-1. Intracluster correlations for PSUs and SSUs (continued)

| Subgroup | Outcome | Adjustment for weight variation | | Cases assigned average weight | |
|---|---|---|---|---|---|
| | | $\rho_1$ | $\rho_2$ | $\rho_1$ | $\rho_2$ |
| **Metro/non-metro** | | | | | |
| Metro | FAFH | 0.00 | 0.05 | 0.01 | 0.05 |
| Non-metro | FAFH | 0.02 | 0.01 | -0.02 | 0.01 |
| Metro | FAH | 0.02 | 0.10 | 0.00 | 0.07 |
| Non-metro | FAH | 0.05 | 0.06 | 0.01 | 0.02 |
| Metro | Free items | 0.03 | 0.09 | 0.01 | 0.03 |
| Non-metro | Free items | 0.04 | 0.06 | 0.04 | 0.05 |
| Metro | Food insecurity | 0.02 | 0.11 | 0.02 | 0.06 |
| Non-metro | Food insecurity | 0.01 | 0.08 | 0.03 | 0.03 |
| **Rural/non-rural** | | | | | |
| Non-rural | FAFH | 0.00 | 0.06 | 0.00 | 0.05 |
| Rural | FAFH | 0.03 | 0.05 | 0.03 | 0.06 |
| Non-rural | FAH | 0.00 | 0.11 | 0.00 | 0.07 |
| Rural | FAH | 0.02 | 0.10 | 0.03 | 0.04 |
| Non-rural | Free items | 0.04 | 0.06 | 0.01 | 0.04 |
| Rural | Free items | 0.04 | 0.14 | 0.02 | 0.03 |
| Non-rural | Food insecurity | 0.03 | 0.10 | 0.02 | 0.07 |
| Rural | Food insecurity | 0.00 | 0.12 | 0.01 | 0.04 |

households, and the right-most columns in Table 3-1 provide the resulting intracluster correlations, which are generally smaller than the results from the approach that adjusts the intracluster correlations for the differential weights. Table 3-1 shows that, overall, the values of $\rho_1$ range from 0.00 to 0.02 across the four outcome variables. This means that the between PSU variance component is small, and that the number of PSUs and the level of stratification may be adequate. The values of $\rho_2$ range from 0.05 to 0.10 across the four outcome variables. This means that the between SSU variance component is larger than the between PSU variance component. This result can be expected, because smaller clusters are naturally more likely to have similar characteristics among households than larger clusters. When considering the clustering impact, that is when computing the DEFF due to clustering, it is noted from equation (1) that the $DEFF_{CLU}$ is computed with a sample size within PSUs eight times that of the SSU, and, therefore, the intraPSU correlation ($\rho_1$) has more impact in the DEFF computation.

Clustering can occur by subgroup; for example, the clustering impact for SNAP is in general less extreme than for non-SNAP groups, and clustering for Target Group A (and B to a certain extent) appears more extreme than for other groups. The intracluster correlations are slightly larger and slightly more variable for rural/non-rural subgroups, and metro/non-metro subgroups, with a maximum value of $\rho_1$ = 0.05 and 0.14 for $\rho_2$. The correlations are quite a bit more variable and larger for target groups and among WIC households. The correlations for subgroups are likely imprecise for rural, non-metro, and maybe WIC.

By inserting the average sample sizes and the values for the intracluster correlations into equation (1), the values of $DEFF_{CLU}$ are estimated as given in Table 3-2. We focus mainly on the $DEFFs$ using the adjustment to remove the weighting impact (column "Adjustment for weight variation"). The values of $DEFF_{CLU}$ range from 1.94 for FAFH expenditures to 4.18 for the number of free food items obtained. For each outcome variable, the values of $DEFF_{CLU}$ are generally lower for subgroups. The exceptions are for:

- FAFH for Target Groups B and D;
- FAH for WIC/nonWIC HH classification and metro/non-metro classification;
- Free items for metro and non-rural; and
- Food insecurity for metro and non-rural.

Among target groups, the values of $DEFF_{CLU}$ are generally highest in Target Group C and metro classification with the exception of FAFH.

Table 3-2. Values of $DEFF_{CLU}$ for outcome variables, by subgroups

| Subgroup | Outcome | Sample size | Number of PSUs with respondent HHs | Number of SSUs with respondent HHs | Average number of HHs per PSU | Average number of HHs per SSU | $DEFF_{CLU}$ Adjustment for weight variation | $DEFF_{CLU}$ Cases assigned average weight |
|---|---|---|---|---|---|---|---|---|
| **Overall** | | | | | | | | |
| | FAFH | 4,660 | 50 | 395 | 93.2 | 11.8 | 1.94 | 2.11 |
| | FAH | 4,699 | 50 | 395 | 94.0 | 11.9 | 2.78 | 1.95 |
| | Free items | 4,739 | 50 | 395 | 94.8 | 12.0 | 4.18 | 2.58 |
| | Food insecurity | 4,826 | 50 | 395 | 96.5 | 12.2 | 3.67 | 3.27 |
| **Target Group** | | | | | | | | |
| A | FAFH | 328 | 47 | 192 | 7.0 | 1.7 | 0.66 | 0.76 |
| B | FAFH | 825 | 50 | 309 | 16.5 | 2.7 | 2.12 | 0.83 |
| C | FAFH | 1,975 | 50 | 369 | 39.5 | 5.4 | 1.88 | 1.40 |
| D | FAFH | 1,532 | 50 | 333 | 30.6 | 4.6 | 1.99 | 1.52 |
| A | FAH | 330 | 47 | 192 | 7.0 | 1.7 | 2.08 | 1.53 |
| B | FAH | 829 | 50 | 309 | 16.6 | 2.7 | 2.05 | 1.24 |
| C | FAH | 2,011 | 50 | 369 | 40.2 | 5.4 | 2.25 | 1.24 |
| D | FAH | 1,529 | 50 | 333 | 30.6 | 4.6 | 1.96 | 1.51 |
| A | Free items | 339 | 47 | 192 | 7.2 | 1.8 | 1.71 | 0.87 |
| B | Free items | 839 | 50 | 309 | 16.8 | 2.7 | 2.37 | 1.62 |
| C | Free items | 2,034 | 50 | 369 | 40.7 | 5.5 | 3.34 | 1.83 |
| D | Free items | 1,527 | 50 | 333 | 30.5 | 4.6 | 1.48 | 1.74 |
| A | Food insecurity | 346 | 47 | 192 | 7.4 | 1.8 | 1.21 | 1.21 |
| B | Food insecurity | 851 | 50 | 309 | 17.0 | 2.8 | 1.15 | 1.09 |
| C | Food insecurity | 2,048 | 50 | 369 | 41.0 | 5.6 | 2.25 | 1.39 |
| D | Food insecurity | 1,581 | 50 | 333 | 31.6 | 4.7 | 1.92 | 0.89 |
| **WIC HH Classification** | | | | | | | | |
| Non-WIC | FAFH | 523 | 50 | 253 | 10.5 | 2.1 | 1.08 | 0.82 |
| WIC | FAFH | 442 | 50 | 217 | 8.8 | 2.0 | 1.79 | 1.03 |
| Non-WIC | FAH | 535 | 50 | 253 | 10.7 | 2.1 | 2.88 | 1.22 |
| WIC | FAH | 447 | 50 | 217 | 8.9 | 2.1 | 3.06 | 1.44 |
| Non-WIC | Free items | 541 | 50 | 253 | 10.8 | 2.1 | 2.36 | 1.45 |
| WIC | Free items | 456 | 50 | 217 | 9.1 | 2.1 | 1.47 | 1.13 |
| Non-WIC | Food insecurity | 546 | 50 | 253 | 10.9 | 2.2 | 1.84 | 1.23 |
| WIC | Food insecurity | 461 | 50 | 217 | 9.2 | 2.1 | 3.10 | 2.31 |

Table 3-2. Values of $DEFF_{CLU}$ for outcome variables, by subgroups (continued)

| Subgroup | Outcome | Sample size | Number of PSUs with respondent HHs | Number of SSUs with respondent HHs | Average number of HHs per PSU | Average number of HHs per SSU | $DEFF_{CLU}$ | |
|---|---|---|---|---|---|---|---|---|
| | | | | | | | Adjustment for weight variation | Cases assigned average weight |
| **Metro/non-metro** | | | | | | | | |
| Metro | FAFH | 4,248 | 50 | 349 | 85.0 | 12.2 | 1.84 | 2.12 |
| Non-metro | FAFH | 412 | 14 | 45 | 29.4 | 9.2 | 1.68 | 0.63 |
| Metro | FAH | 4,286 | 50 | 349 | 85.7 | 12.3 | 3.51 | 2.15 |
| Non-metro | FAH | 413 | 14 | 45 | 29.5 | 9.2 | 2.79 | 1.34 |
| Metro | Free items | 4,331 | 50 | 349 | 86.6 | 12.4 | 4.28 | 2.47 |
| Non-metro | Free items | 408 | 14 | 45 | 29.1 | 9.1 | 2.62 | 2.54 |
| Metro | Food insecurity | 4,400 | 50 | 349 | 88.0 | 12.6 | 4.38 | 3.70 |
| Non-metro | Food insecurity | 426 | 14 | 45 | 30.4 | 9.5 | 2.04 | 2.19 |
| **Rural/non-rural** | | | | | | | | |
| Non-rural | FAFH | 3,395 | 48 | 283 | 70.7 | 12.0 | 1.33 | 1.61 |
| Rural | FAFH | 1,265 | 37 | 128 | 34.2 | 9.9 | 2.60 | 2.50 |
| Non-rural | FAH | 3,420 | 48 | 283 | 71.3 | 12.1 | 2.32 | 2.05 |
| Rural | FAH | 1,279 | 37 | 128 | 34.6 | 10.0 | 2.52 | 2.23 |
| Non-rural | Free items | 3,452 | 48 | 283 | 71.9 | 12.2 | 4.31 | 2.21 |
| Rural | Free items | 1,287 | 37 | 128 | 34.8 | 10.1 | 3.65 | 1.74 |
| Non-rural | Food insecurity | 3,515 | 48 | 283 | 73.2 | 12.4 | 4.33 | 3.61 |
| Rural | Food insecurity | 1,311 | 37 | 128 | 35.4 | 10.2 | 2.11 | 1.70 |

The results of the clustering impact analysis shows a non-negligible impact of clustering, which exists in other in-person household surveys. A large value of the intracluster correlation for PSUs would point to the need for more PSUs, and/or larger PSUs, in the sample. Likewise, if the intracluster correlation for SSUs is large, then a larger number of SSUs, and/or larger SSUs, may be considered. The population and geographic sizes of the PSUs and SSUs for FoodAPS-1 are at about the maximum size used in surveys, and, therefore, the choice is whether or not to increase the numbers of PSUs and the numbers of SSUs to reduce clustering. Another key factor in arriving at the number of PSUs and SSUs is cost, such as the cost of travel within clusters by interviewers and the hiring of more interviewers.

Overall, when considering the values of the intracluster correlations and design effects due to clustering, the size and number of PSUs and SSUs appear to be reasonable. Likewise, by subgroups, especially by target group and for WIC household classification, the size and number of PSUs and SSUs appear to be reasonable. To reduce the clustering in metro areas, more SSUs could be selected. There are several trade-offs to consider. If the stratification of PSUs can be improved, forming small PSUs may be justified, which would help to decrease cost and potentially improve response rates due to less travel within the PSU. However, the instability of the intracluster correlations remains a concern due to the low numbers of degrees of freedom, which is driven by the number of PSUs.

# 4 Design Effect Due to Stratification

The FoodAPS-1 non-certainty PSUs were selected systematically from a sorted list with probability proportionate to size. The list was sorted by metropolitan status and region, which acts as implicit stratification, which typically will reduce the between PSU variance if the sort order variables are associated with the outcome variables. To evaluate the impact of stratification, the impact ratio was defined as:

$$Impact\ ratio = \frac{Estimated\ variance\ with\ stratification}{Estimated\ variance\ without\ stratification}$$

In general, if stratification were effective, the impact ratio as defined above would have values less than 1. Estimation of the numerator was facilitated by the actual variance estimation codes in FoodAPS. That is, the numerator was estimated using Taylor Linearization using the FoodAPS-1 variance estimation codes for strata (JKSTRATA) and clusters (JKPSU). In this manner, the strata reflect the certainty PSU, as well as the pairing of noncertainty PSUs according to the sort order of PSU selection. Due to the odd number of non-certainty PSUs, there was one variance strata with three PSUs. For the certainty PSU, the variance units were the eight SSUs. The variance units were the PSUs in the noncertainty strata.

The denominator was estimated by redefining the variance strata to produce variance estimates as if no stratification were done. That is, there were two variance strata assigned: one reflected the certainty PSU, and the second was made up of the set of noncertainty PSUs. As above, for the certainty PSU, the variance units were the eight SSUs. In the single noncertainty stratum, the variance units were the PSUs. With this approach, however, we caution that the impact rate will overestimate the denominator due to the designed dispersion caused from the selection of the PSUs.

Tables 4-1 through 4-5 provide the impact ratios due to stratification for each outcome measure, overall, and by each subgroup.

Table 4-1. Impact ratio due to stratification for outcome measures, overall

| Outcome of interest | Estimate | Standard error (with stratification) | Standard error (without stratification) | Impact ratio |
|---|---|---|---|---|
| Total Food At Home | 105.72 | 2.90 | 3.48 | 0.69 |
| Total Food Away from Home | 56.52 | 1.61 | 2.64 | 0.37 |
| Total Free Events | 3.02 | 0.14 | 0.11 | 1.53 |
| Food Insecurity | 0.16 | 0.01 | 0.01 | 0.79 |

Table 4-2. Impact ratio due to stratification for outcome measures, by target group

| Outcome of interest | Estimate | Standard error (with stratification) | Standard error (without stratification) | Impact ratio |
|---|---|---|---|---|
| **Total Food At Home** | | | | |
| Group A | 67.51 | 6.24 | 6.01 | 1.08 |
| Group B | 72.55 | 3.48 | 3.72 | 0.87 |
| Group C | 116.67 | 3.73 | 4.14 | 0.81 |
| Group D | 94.14 | 4.06 | 4.43 | 0.84 |
| **Total Food Away from Home** | | | | |
| Group A | 30.43 | 4.80 | 5.00 | 0.92 |
| Group B | 34.37 | 3.00 | 3.32 | 0.81 |
| Group C | 67.55 | 2.20 | 3.19 | 0.48 |
| Group D | 30.99 | 2.14 | 2.30 | 0.86 |
| **Total Free Events** | | | | |
| Group A | 2.47 | 0.35 | 0.35 | 0.98 |
| Group B | 2.61 | 0.22 | 0.18 | 1.47 |
| Group C | 2.96 | 0.17 | 0.15 | 1.31 |
| Group D | 3.96 | 0.18 | 0.20 | 0.84 |
| **Food Insecurity** | | | | |
| Group A | 0.42 | 0.03 | 0.04 | 0.54 |
| Group B | 0.03 | 0.02 | 0.02 | 0.61 |
| Group C | 0.07 | 0.01 | 0.01 | 1.23 |
| Group D | 0.45 | 0.02 | 0.02 | 0.90 |

Table 4-3. Impact ratio due to stratification for outcome measures, by WIC household classification

| Outcome of interest | Estimate | Standard error (with stratification) | Standard error (without stratification) | Impact ratio |
|---|---|---|---|---|
| **Total Food At Home** | | | | |
| non-WIC | 147.95 | 10.85 | 11.06 | 0.96 |
| WIC | 116.93 | 8.77 | 8.01 | 1.20 |
| **Total Food Away from Home** | | | | |
| non-WIC | 65.42 | 3.95 | 4.49 | 0.77 |
| WIC | 55.59 | 5.42 | 4.86 | 1.24 |
| **Total Free Events** | | | | |
| non-WIC | 4.50 | 0.41 | 0.35 | 1.37 |
| WIC | 4.96 | 0.40 | 0.44 | 0.83 |
| **Food Insecurity** | | | | |
| non-WIC | 0.15 | 0.03 | 0.03 | 1.19 |
| WIC | 0.30 | 0.04 | 0.04 | 1.32 |

Universe: someone in HH AGE = 14 – 49 and SEX = 2 and ANYPREGNANT = 1, or someone in the household under age 5.

Table 4-4. Impact ratio due to stratification for outcome measures, by metro/non-metro classification

| Outcome of interest | Estimate | Standard error (with stratification) | Standard error (without stratification) | Impact ratio |
|---|---|---|---|---|
| **Total Food At Home** | | | | |
| non-Metro | 107.87 | 3.49 | 3.98 | 0.77 |
| Metro | 91.85 | 7.58 | 6.53 | 1.35 |
| **Total Food Away from Home** | | | | |
| non-Metro | 59.56 | 1.71 | 2.60 | 0.43 |
| Metro | 37.06 | 3.20 | 3.16 | 1.03 |
| **Total Free Events** | | | | |
| non-Metro | 3.09 | 0.14 | 0.11 | 1.47 |
| Metro | 2.57 | 0.35 | 0.34 | 1.04 |
| **Food Insecurity** | | | | |
| non-Metro | 0.16 | 0.01 | 0.01 | 0.18 |
| Metro | 0.14 | 0.02 | 0.02 | 0.33 |

Table 4-5. Impact ratio due to stratification for outcome measures, by rural/non-rural classification

| Outcome of interest | Estimate | Standard error (with stratification) | Standard error (without stratification) | Impact ratio |
|---|---|---|---|---|
| **Total Food At Home** | | | | |
| non-Rural | 104.29 | 2.89 | 3.97 | 0.53 |
| Rural | 108.53 | 5.51 | 6.06 | 0.83 |
| **Total Food Away from Home** | | | | |
| non-Rural | 59.68 | 1.65 | 2.94 | 0.32 |
| Rural | 50.28 | 3.15 | 3.54 | 0.79 |
| **Total Free Events** | | | | |
| non-Rural | 3.04 | 0.15 | 0.12 | 1.71 |
| Rural | 2.98 | 0.25 | 0.23 | 1.18 |
| **Food Insecurity** | | | | |
| non-Rural | 0.18 | 0.01 | 0.01 | 0.75 |
| Rural | 0.13 | 0.01 | 0.01 | 0.80 |

The results are mixed. Overall, the impact ratio associated with free items is 1.53, but is less than 1 for the other three outcome measures. Among target groups, the impact ratios for Target Group D is less than 1 for all outcome measures. For households classified as WIC, only free items had impact ratios less than 1. For metro/non-metro status, the impact ratios values for food insecurity are well below 1. For rural/non-rural status, all impact ratios values are less than 1 except for free items.

Due to the low number of degrees of freedom (approximately 25 to 31 for FoodAPS-1 depending on how they are counted), the ratios are unstable. Degrees of freedom are an indication of the stability of the variance estimates (e.g., the variance associated with the variance estimates. Another reason for the mixed results could be due to the variables used in the stratification (sort order). As mentioned in Section 1.2, prior to selection, the PSUs were sorted by metropolitan status and region. To improve upon the impact of stratification, other variables could be investigated that may be more strongly associated with the outcome measures, such as poverty, income, and SNAP rates.

# Concluding Remarks 5

The evaluation of the FoodAPS-1 sample design serves the purpose of informing an improved design for the next survey. In general, large variability in the weights was observed, which impacted the resulting precision of estimates. Variability across target groups is by design, but a great amount of within-group variability is problematic. Part of the weight variation issue is misclassification (differences in classification among the SNAP lists, screener, and main study), and the way the sample was released. Also, the design proved challenging as illustrated by the actual sample sizes for Target Groups A and B falling far short of the target sample sizes. The evaluation was organized by three main aspects of the design: (1) stratification, (2) clustering, and (3) differential weights.

In general, the stratification impact was mixed; however, future design work should explore the benefits of explicit stratification of PSUs versus the use of the composite MOS. The sorting variables used in FoodAPS-1 were metro status and FNS region. Use of other potential stratification variables, such as percentage in poverty, may provide a better chance at arriving at desired sample sizes for Target Groups A and B, and may provide more potential to reduce the resulting variance to get more power out of the survey cases. Future design work should explore the benefits of using the composite MOS, as well as the best sources for the stratification and MOS, variables. The planning should explore the pros and cons of the composite MOS, when stratification of SNAP lists will occur within the SSUs.

The clustering amounts in FoodAPS-1 are about as expected. The size of the FoodAPS-1 PSUs and SSUs are among the largest in use by in-person surveys, which results in low impact on variances from clustering. However, it also increases travel time by interviewers and may increase costs as well as decrease response rates. In terms of PSUs and SSUs, future design work should incorporate the estimated intracluster correlations in this report to gauge the number to select, and take into consideration other ways to form PSUs. For example, PSUs can be formed from counties where contiguous counties can be combined to reach a minimum population size of 15,000. In addition, the number of degrees of freedom for statistical analysis should be taken into consideration, which can be increased by increasing the number of first-stage units.

Among the three main aspects that impact the resulting variances, the most potential for improvement is by reducing the weight variation. Future design work should ensure protocols to

eliminate or limit the increased amount of weight variation when handling drop points in the ABS, updating the address lists, and when releasing reserve sample to address shortfalls. Ways should be sought to reduce weight variation within target groups through the sampling process and minimizing misclassification. In addition, other domains, such as incorporating WIC in the definition of target groups, will be explored with the assignment of sampling rates in the sampling plan for the next main survey.

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# Appendix A

# Sampling Error Measures

# Appendix A
# Sampling Error Measures

There are several measures of precision used for evaluating sample designs and variances. The standard error *(SE)*, or the square root of the estimated variance of the point estimate, is a basic measure of the sampling error. Under simple random sampling ($SRS$), for an estimate of a proportion $p$, the $SE$ is computed as $SE(p) = \sqrt{p(1-p)/n}$, where $n$ is the sample size. The $SE$ formula given above is for $SRS$ but in practice, large-scale national surveys, such as FoodAPS-1, typically employ complex sample designs. Conceptually, the $SE$ formula for $SRS$ needs to be multiplied by the square root of the design effect ($DEFF$) to give the $SE$ under the complex design. The $DEFF$ is a useful quantity to examine when comparing alternative designs. The $DEFF$ is computed as:

$$DEFF = \frac{Estimated\ variance\ under\ complex\ design}{Estimated\ variance\ under\ SRS}$$

Since the FoodAPS-1 design consists of a multistage cluster sample, the $SE$ is typically larger than under $SRS$. One interpretation of $DEFF$ says that if $DEFF = 2$, the sample size needs to be doubled to achieve the same precision as from an $SRS$. Another interpretation is that if the resulting sample size from the complex sample is 5,000 respondents, then with a $DEFF = 2$, the effective sample size is 2,500. Another way of way of looking at it, if the variance is estimated with an SRS formula, and if *DEFF = 2*, then the resulting *SE* needs to be increased by about 41 percent.

The *CV* is another common measure of precision, which is sometimes referred to as the relative standard error. The *CV* is computed as the ratio of the standard error to the point estimate (e.g., *p*). The *CV* is especially useful when estimating means, but it is a bit problematic when estimating low or high proportions. For example, under *SRS* of size 100, for an estimated proportion *p* = 0.025 for a particular attribute, the *SE* is 0.016, and the *CV* is 62.4 percent. However, for the complement of the attribute (1-*p*) equaling 0.975, the *SE* is still 0.016, and the *CV* is only 1.6 percent.

# Appendix B

# Intracluster Correlation Computations

# Appendix B
# Intracluster Correlation Computations

To estimate $\rho_1$ and $\rho_2$, we first decompose the total variance into three between-variance terms attributable to Primary Sampling Units (PSUs), Secondary Sampling Units (SSUs), and households (HHs) as follows:

$$\sigma_T^2 = \sigma_{PSU}^2 + \sigma_{SSU(PSU)}^2 + \sigma_{HH(SSU)}^2$$

The intracluster correlation within the PSU is computed as:

$$\rho_1 = \frac{\sigma_{PSU}^2}{\sigma_{PSU}^2 + \sigma_{SSU(PSU)}^2 + \sigma_{HH(SSU)}^2}$$

The intracluster correlation for individuals within the SSU is computed as:

$$\rho_2 = \frac{\sigma_{SSU(PSU)}^2}{\sigma_{SSU(PSU)}^2 + \sigma_{HH(SSU)}^2}$$

The following explains how to compute the terms in the above formulas for the intracluster correlations. The variance of an estimate $(\hat{\theta})$ can be decomposed as:

$$Var(\hat{\theta}) = \frac{\sigma_{PSU}^2}{n_{PSU}} + \frac{\sigma_{SSU(PSU)}^2}{n_{SSU}} + \frac{\sigma_{HH(SSU)}^2}{n_{HH}} \quad (2)$$

The first term in (2) is:

$\frac{\sigma_{PSU}^2}{n_{PSU}} = Var(\hat{\theta})^{NSR^*} - Var(\hat{\theta})^{SSU^*}$, and therefore
$\sigma_{PSU}^2 = n_{PSU}[Var(\hat{\theta})^{NSR^*} - Var(\hat{\theta})^{SSU^*}]$

where,

$Var(\hat{\theta})^{NSR^*} = \frac{Var(\hat{\theta})^{NSR}}{1+cv_{w_{PSU}}^2}$, where $Var(\hat{\theta})^{NSR}$ is the sampling variance of $\hat{\theta}$ among non-self-representing PSUs, and

$Var(\hat{\theta})^{SSU^*} = \frac{Var(\hat{\theta})^{SSU}}{1+cv^2_{\bar{w}_{SSU}}}$, where $Var(\hat{\theta})^{SSU}$ is the between SSU variance of $\hat{\theta}$.

The variance $Var(\hat{\theta})^{NSR}$ was estimated among the 49 non-certainty PSUs using Taylor Linearization with the variance strata assigned using the available JKSTRATA variable, and the variance units assigned as the PSUs, as given in the JKPSU variable. The JKSTRATA variable mainly comprises PSUs paired in the sorted order of selection.

The variance $Var(\hat{\theta})^{SSU}$ was estimated among the 50 PSUs using Taylor Linearization with the variance strata assigned as PSUs, and the variance units assigned as the SSUs.

For the second term in (2),

$\frac{\sigma^2_{SSU(PSU)}}{n_{SSU}} = Var(\hat{\theta})^{SSU^*} - Var(\hat{\theta})^{HH^*}$, and therefore,
$\sigma^2_{SSU(PSU)} = n_{SSU}[Var(\hat{\theta})^{SSU^*} - Var(\hat{\theta})^{HH^*}]$

where,

$Var(\hat{\theta})^{HH^*} = \frac{Var(\hat{\theta})^{HH}}{1+cv^2_{w_{HH}}}$, where $Var(\hat{\theta})^{HH}$ is the between HH variance of $\hat{\theta}$.

The variance $Var(\hat{\theta})^{HH}$ was estimated among the 50 PSUs using Taylor Linearization with the variance strata assigned as SSUs, and the variance units assigned as the HHs.

For the third term in (2), $\frac{\sigma^2_{HH(SSU)}}{n_{HH}} = Var(\hat{\theta})^{HH^*}$, and therefore,
$\sigma^2_{HH(SSU)} = n_{HH}Var(\hat{\theta})^{HH^*}$.

As shown above, the variance component at each stage was divided by the $DEFF_{UEW}$ component. The $DEFF_{UEW}$ component was computed as a function of the variance of the average weight at each stage. That is, at each stage of selection, the design effect due to the weight variation was computed as follows:

$$cv^2_{\bar{w}_{PSU}} = \frac{Var(\bar{w}_{PSU})}{\bar{w}_{PSU}}$$

where,

$Var(\bar{w}_{PSU}) = \frac{\sum_i (\bar{w}_i - \bar{w}_{PSU})^2}{n_{PSU}-1}$, $\bar{w}_{PSU} = \frac{\sum \bar{w}_i}{n_{PSU}}$, and where $\bar{w}_i =$ average HH weight for $PSU_i$

At the second stage,

$$cv^2_{\bar{w}_{SSU}} = \frac{Var(\bar{w}_{SSU})}{\bar{w}_{SSU}},$$

where,

$Var(\bar{w}_{SSU}) = \frac{\sum_{ij} (\bar{w}_{ij} - \bar{w}_{SSU})^2}{n_{SSU}-1}$, $\bar{w}_{SSU} = \frac{\sum_{ij} \bar{w}_{ij}}{n_{SSU}}$, and where
$\bar{w}_{ij} =$ average HH weight for $SSU_j \; in \; PSU_i$.

At the third stage,

$$cv^2_{\bar{w}_{HH}} = \frac{Var(w_{HH})}{\bar{w}_{HH}}$$

where,

$$Var(w_{HH}) = \frac{\sum_{ijk} (w_{ijk} - \bar{w}_{HH})^2}{n_{HH}-1}, \text{ and } \bar{w}_{HH} = \frac{\sum_{ijk} w_{ijk}}{n_{HH}}.$$