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REPORT

FINAL REPORT

National Beneficiary Survey–General Waves Round 5: Nonresponse Bias Analysis

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TABLES

ACRONYMS

AIC	Akaike's Information Criterion
AHRF	Area Health Resource File
CAPI	Computer Assisted Personal Interviewing
CATI	Computer Assisted Telephone Interviewing
CHAID	Chi-Squared Automatic Interaction Detector
DCF	Disability Control File
FRA	Full Retirement Age
NBS	National Beneficiary Survey
OMB	Office of Management and Budget
PSU	Primary Sampling Unit
RBS	Representative Beneficiary Sample
SPSS	Statistical Package for the Social Sciences (SPSS is a registered trademark of SPSS, Inc., Chicago, IL)
SSA	Social Security Administration
SSDI	Social Security Disability Insurance (Title II of the Social Security Act)
SSI	Supplemental Security Income (Title XVI of the Social Security Act)
SSU	Secondary Sampling Unit
SWS	Successful Worker Sample

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NBS DATA DOCUMENTATION REPORTS

The following reports make up the documentation describing the NBS, the 2015 data collection effort, and the data files and are available on SSA's website: (https://www.ssa.gov/disabilityresearch/nbs_round_5.htm#general):

- **User's Guide for Restricted- and Public-Use Data Files** (Wright et al. 2017). This report provides users with information about the restricted- and public-use data files, including construction of the files; weight specification and variance estimation; masking procedures employed in the creation of the Public-Use File; and a detailed overview of the questionnaire design, sampling, and NBS—General Waves data collection. The report provides information covered in the Editing, Coding, Imputation, and Weighting Report and the Cleaning and Identification of Data Problems Report (described below), including procedures for data editing, coding of open-ended responses, and variable construction, and a description of the imputation and weighting procedures and development of standard errors for the survey.
- **NBS—General Waves Public-Use File Codebook** (Bush et al. 2017). This codebook provides extensive documentation for each variable in the file, including variable name, label, position, variable type and format, question universe, question text, number of cases eligible to receive each item, constructed variable specifications, and user notes for variables on the public-use file. The codebook also includes frequency distributions and arithmetic means as appropriate.
- **NBS–General Waves Questionnaire** (Barrett et al. 2016). This document contains all questionnaire items used in Round 5 of the NBS—General Waves and includes documentation of skip patterns, question universe specifications, text fills, interviewer directives, and consistency and range checks.
- **Editing, Coding, Imputation, and Weighting Report** (Grau et al. 2017). This report summarizes the editing, coding, imputation, and weighting procedures as well as the development of standard errors for Round 5 of the NBS—General Waves. It includes an overview of the variable naming, coding, and construction conventions used in the data files and accompanying codebooks; describes how the sampling weights were computed to the final post-stratified analysis weights for both the Representative Beneficiary Sample; outlines the procedures used to impute missing responses; and discusses procedures that should be used to estimate sampling variances for the NBS—General Waves.
- **Cleaning and Identification of Data Problems Report** (Skidmore et al.2017). This report describes the data processing procedures performed for Round 5 of the NBS—General Waves. It outlines the data coding and cleaning procedures and describes data problems, their origins, and the corrections implemented to create the final data file. The report describes data issues by sections of the interview and concludes with a summary of types of problems encountered and general recommendations.
- **NBS—General Waves Nonresponse Bias Analysis (current report).** The purpose of this report is to determine if the nonresponse adjustments applied to the sampling weights of Round 5 of the NBS—General Waves appropriately account for differences between respondents and nonrespondents, or if the potential for nonresponse bias still exists.

The following restricted-use report is available from SSA through a formal data sharing agreement:

- **NBS Restricted-Access Codebook (Bush et al. 2017)**. This codebook provides extensive documentation for each variable in the file, including variable name, label, position, variable type and format, question universe, question text, number of cases eligible to receive each item, constructed variable specifications, and user notes for variables on the restricted-access file. The codebook also includes frequency distributions and means as appropriate.

INTRODUCTION

In all studies, final survey estimates are based solely on respondents. Errors may arise in the estimates resulting from unit nonresponse if there are systematic differences between individuals who respond to a survey and those who do not. Nonresponse-adjusted weights attempt to account for these differences identifying respondents and nonrespondents who are similar on characteristics available for both, and adjusting the weights of the respondents to compensate for the nonrespondents. Insofar as these adjustments are able to account completely for differences between nonrespondents and respondents, survey estimates would have minimal potential for nonresponse bias.

The purpose of this report is to determine if the nonresponse adjustments applied to the sampling weights of Round 5 of the National Beneficiary Survey General Waves (NBS—General Waves) effectively account for differences between respondents and nonrespondents, or if the potential for nonresponse bias still exists.

Our analysis indicates that the nonresponse adjustment alleviated all differences observed between respondents and nonrespondents in the beneficiary sample for the variables that we had at our disposal.

A. Study Overview

As part of the NBS—General Waves, Mathematica Policy Research conducted the first of three new rounds of data collection in 2015, with two additional rounds to be administered in 2017 and 2019. The survey was sponsored by the Social Security Administration's (SSA) Office of Retirement and Disability Policy and data were collected from a national sample of SSA disability beneficiaries.

The prior rounds of the NBS—conducted by SSA in 2004, 2005, 2006, and 2010[1]—took an important first step toward understanding the work interest and experiences of Supplemental Security Income (SSI) recipients and Social Security Disability Insurance (SSDI) beneficiaries. These surveys helped glean information about beneficiary impairments; health; living arrangements; family structure; occupation before disability; and use of non-SSA programs (for example, the Supplemental Nutrition Assistance Program, or SNAP). The prior NBS rounds also evaluated the Ticket to Work and Self-Sufficiency (TTW) program. The NBS–General Waves no longer includes a focus on TTW. Instead, through the survey, we seek to uncover important information about the factors that promote beneficiary self-sufficiency and, conversely, the factors that impede beneficiary efforts to maintain employment.

The NBS—General Waves collects important beneficiary data that are not available from SSA administrative data or other sources, including more detailed information about their disabilities other than their general disability classification and disability payment information, interest in work, use of services, and employment.

[1] In this report, we refer to the NBS rounds conducted in 2004, 2005, 2006, 2010, and 2015 as Round 1, Round 2, Round 3, Round 4, and Round 5, respectively. We refer to the planned 2017 and 2019 rounds as Round 6 and Round 7, respectively.

The survey addresses five major questions:

1. What are the work-related goals and activities of Supplemental Security Income (SSI) and Social Security Disability Insurance (SSDI) beneficiaries, particularly as they relate to long-term employment?
2. What are the short-term and long-term employment outcomes for SSI and SSDI beneficiaries who work?
3. What supports help SSA beneficiaries with disabilities find and keep jobs and what barriers to work do they encounter?
4. What are the characteristics and experiences of beneficiaries who work?
5. What health-related factors, job-related factors, and personal circumstances hinder or promote employment and self-sufficiency?

SSA will combine data from Round 5 of the NBS—General Waves with SSA administrative data to provide critical information on access to jobs and employment outcomes for beneficiaries. As a result, SSA and external researchers who are interested in disability and employment issues may use the survey data for policymaking and program planning efforts. In this report, we first describe the sample design and the population that the sample is supposed to represent, followed by a description of the nonresponse adjustments to the sampling weights. We then provide the unweighted and weighted response rates for the beneficiary sample and its substrata. In Tables 4, 5, and 6, we assess (1) how well the sample represents the data from the sampling frame, (2) how ineligible sample cases differ from the entire population, (3) how sample respondents differ from nonrespondents, and (4) how well non-response adjusted weights account for these differences, using the initial unadjusted weights and weights adjusted for nonresponse. The comparison between the estimates with adjusted and unadjusted weights allows us to (1) see the potential for nonresponse bias after removing nonrespondents and making no nonresponse adjustments to the weights and (2) assess the effectiveness of nonresponse adjustment procedures on the potential for nonresponse bias.

1. Target Population and Sample Design

The target population of the NBS—General Waves includes SSI and SSDI beneficiaries between the ages of 18 and full retirement age (FRA). It included beneficiaries, from all 50 states and the District of Columbia, who were in active pay status[2] as of June 2014, which consisted of approximately 13.8 million persons.[3] Because of the availability of administrative data for all SSI and SSDI beneficiaries, we were able to ascertain many of the "true" properties of the target population, providing tools for the processing of this analysis.

The eventual goal of the NBS—General Waves will be to obtain information from two surveys, one of all beneficiaries (the Representative Beneficiary Sample, or RBS) and one limited to beneficiaries who had monthly earnings that were high enough and sustained over a

[2] Active status includes beneficiaries who are currently receiving cash benefits as well as those whose benefits have been temporarily suspended for work or other reasons. It does not include beneficiaries whose benefits have been terminated.

[3] The target population excludes beneficiaries living in Puerto Rico or other outlying territories.

long enough period of time to be considered "successful workers." A sample of the latter group, called the Successful Workers Sample (SWS), will be conducted in Rounds 6 and 7 of the NBS—General Waves, but not in Round 5.[4] From this point forward, this report will focus on the potential for nonresponse bias in the RBS.

The NBS—General Waves used a multistage sampling design in all survey rounds. For the multistage design, Mathematica used data from SSA on the counts of eligible beneficiaries in each county within four age strata (18 to 29 years, 30 to 39 years, 40 to 49 years, and 50 years and older) to form primary sampling units (PSU) consisting of one or more counties. The PSUs selected at Round 5 were the first-stage sampling units for all subsequent rounds. We selected a sample of PSUs from an exhaustive list of 1,330, using a composite measure of size calculated from the most recent counts of beneficiaries in the four age strata. We classified two PSUs as certainty selections (Los Angeles County and Cook County[5]). These counties were certainty selections based on the selection frequencies for the PSUs computed using the composite size measure. Within these counties, we formed secondary sampling units (SSUs) from one or more five-digit ZIP codes within each county, using counts of beneficiaries for the SSUs in each age stratum for the composite size measure, and selected a sample of SSUs within the certainty PSUs. Details on the sample design of the NBS—General Waves, including the selection of PSUs and SSUs, are available in the sampling design section of the User's Guide (Wright et al. 2017).

As shown in Table 1, we selected a sample of 7,682 beneficiaries from strata defined by the four age categories.

Table 1. Round 5 of NBS—General Waves sample sizes, target completes, and actual completes

Sampling Strata	Sample Size	Target Completed Interviews	Actual Completed Interviews
Representative Beneficiary Sample			
Age 18 to 29	2,268	1,111	1,149
Age 30 to 39	2,126	1,111	1,097
Age 40 to 49	2,076	1,111	1,104
Age 50 and older	1,212	667	712
Total Sample Size	7,682	4,000	4,062

Source: Round 5 of NBS—General Waves data collection effort.

[4] The initial NBS—General Waves survey design called for three national cross-sectional surveys of SSI and SSDI beneficiaries (the RBS)—one each in 2014, 2016, and 2018. The NBS—General Waves also called for cross-sectional surveys, in the same years, of beneficiaries whose benefits were suspended or terminated due to work (with a subset followed longitudinally across rounds). However, due to difficulties in identifying beneficiaries experiencing benefit suspense in SSA's administrative data, we subsequently revised the design to focus on beneficiaries with successful work attempts, the successful worker sample (SWS). We delayed the start of Round 5 of the NBS--General Waves by one year to allow time to redesign the successful worker portion of the survey and sample. We excluded the SWS from the Round 5 survey; in its place we conducted semi-structured interviews with 91 successful workers.

[5] Los Angeles County includes the city of Los Angeles; Cook County includes the city of Chicago.

2. Calculation of Nonresponse Adjustments

Each observation had an initial weight that accounted for the sample design. We calculated two adjustments to the weights to account for sample members who did not complete the questionnaire: a location adjustment to compensate for unlocated sample members and, among located cases, a response adjustment to compensate for those who refused to respond. The product of these adjustments, which constitute a nonresponse adjustment to the initial weight, were intended to reduce the potential for bias attributable to differential ability to locate and/or respond, across levels, of a set of auxiliary variables. In this report, we assess whether the adjustments successfully decreased the potential for bias or whether a potential for significant nonresponse bias still exists.

In the absence of information about how nonrespondents would have answered survey questions, we use data from three sources for this analysis: administrative data from the sampling frame provided by the Social Security Administration (SSA), earnings data from the Disability Control File (DCF), also provided by SSA, and data from the Area Health Resource File (AHRF), which contains demographic, health, and economic-related data for every county in the United States (Area Health Resource File 2014–2015). The administrative data included demographic characteristics about each beneficiary, whether they received SSI, SSDI, or both, and their general disability classification and disability payment status, including why and to whom the payments are provided. The DCF earnings data included monthly earnings for each beneficiary for 2013 and 2014, though much of the earnings data, particularly from 2014, was not complete.[6] The AHRF data was used to classify the county where each beneficiary lived and included urbanicity and metropolitan status and information about the county's economic and racial/ethnic characteristics.

We used selected levels of a small number of variables to calculate the nonresponse adjustments. In this analysis, however, we look across all the levels for the variables of greatest interest. We believe that these data provide an effective assessment of the potential for bias in this sample.

3. NBS—General Waves Round 5 Data Collection Effort

In October 2015, Mathematica completed Round 5 of the NBS—General Waves computer-assisted telephone interviewing (CATI) and computer-assisted personal interviewing (CAPI) data collection with interviews for 4,062 individuals in the Representative Beneficiary Sample (RBS). An additional 297 individuals in the Representative Beneficiary Sample were deemed ineligible for the survey.[7] In the RBS, 3,649 interviews were completed by telephone and 413 by

[6] It would generally take approximately three years after the beneficiaries received the earnings for all monthly earnings data to be recorded in the DCF file. By 2016, when this analysis was done, the 2013 earnings data were mostly complete, but the 2014 earnings data were not.

[7] Ineligible sample members included those who were deceased, incarcerated, or no longer living in the continental United States and those whose benefit status was pending. Ineligible cases were treated as respondents for the purposes of weighting, and then the weights were zeroed out at the end of processing. The weighted number of ineligible cases served as an estimate of the number of ineligible cases in the target population.

CAPI.[8] Proxy interviews were completed for 771 sample members. The weighted response rate for the RBS was 62.6 percent.[9]

Despite intensive locating and contact efforts, we achieved response rates that were substantially lower than in prior rounds. There are two main reasons for this: difficulty locating sample members and a higher refusal rate among located beneficiaries. First, even though the contact information was correct for a similar number of cases between Round 5 in 2015 and Round 4 in 2010 (63.8 percent versus 63.0 percent in the prior round), beneficiaries were more difficult to find than in Round 4, with a higher percentage of unlocated cases remaining at the end of data collection (16.2 percent in Round 5, compared to 9.2 percent in Round 4). Second, more beneficiaries refused participation than in prior rounds (13.9 percent in Round 5, compared to 11.5 percent five years earlier in the prior round)

In response to the lower yield rates (the proportion of sample cases that responded to the survey),[10] we applied several strategies to increase the number of completed interviews, including sending prepaid incentives and using in-field locating for cases that could not be located from Mathematica's data collection center. We also considered extending the data collection period to continue our effort on hard-to-reach cases. However, it was determined that extending the data collection period would have increased costs and only marginally increased the number of completes. Hence, we simply increased the sample of cases to ensure these targets would be met. This further suppressed response rates, but it was viewed as a necessary tradeoff to ensure statistical power for analyses.

4. Rationale for Nonresponse Bias Analysis

Because the weighted response rates within strata ranged from 56.5 to 65.5 percent (see Table 2), we conducted a nonresponse bias analysis at the conclusion of data collection, using the full sample of 7,682 sample cases. The purpose of the nonresponse bias analysis was to determine if there were systematic differences between respondents and nonrespondents that could result in a potential for nonresponse bias. This analysis was also conducted in Round 4 of

[8] Of the 3,649 cases completed by CATI, field locators facilitated 932 cases at sample persons' homes.

[9] The response rate is calculated as the weighted count of sample members who completed an interview or were deemed ineligible divided by the weighted sample count of all sample members: (number of completed interviews + number of partially completed interviews + number of ineligibles)/(number of cases in the sample). The response rate is essentially equivalent to the American Association of Public Opinion Research (AAPOR) standard response rate calculation, assuming that all nonrespondents have unknown eligibility status: RR_{AAPOR} = number of completed interviews/(number of cases in the sample - estimated number of ineligible cases). Ineligible cases are included in the numerator and denominator for two reasons: (1) the cases classified as ineligible are part of the original sampling frame (and hence the study population) and we obtained complete information for fully classifying these cases (that is, their responses to the eligibility questions in the questionnaire are complete) such that we may classify them as respondents; and (2) incorporation of the ineligibles into the numerator and denominator of the response rate is essentially equivalent to the definition of a more conventional response rate, assuming that all nonrespondents have unknown eligibility status.

[10] The formula for the (unweighted) yield rate is (number of completed interviews)/(number of sampled cases). Cases that are found to be ineligible during data collection are included in the denominator and excluded from the numerator. The yield rate is necessarily less than or equal to the unweighted response rate.

the prior NBS, even though the response rate in Round 4 was more than 10 percentage points higher, at 72.8 percent.

Table 2. Sample sizes and response rates

	Sample (Unweighted Counts)					Response Rate (Percent)*	
			Nonrespondents				
	Total Sample	Respondents	Located	Unlocated	Ineligibles	Unweighted	Weighted
Beneficiaries	7,682	4,062	2,087	1,236	297	56.7	62.6
Age 18–29	2,268	1,149	580	448	91	54.7	56.5
Age 30–39	2,126	1,097	594	364	71	54.9	57.1
Age 40–49	2,076	1,104	593	297	82	57.1	59.0
Age 50–65	1,212	712	320	127	53	63.1	65.5

* Response rates are calculated by taking the number of respondents and ineligibles as the numerator and dividing by the total number of sample members. Because the eligibility of very few nonrespondents is known, the response rate calculation is close to a more commonly used response rate calculation: numerator = number of respondents and denominator = number of respondents + number of eligible nonrespondents + eligibility rate * number of nonrespondents with unknown eligibility. In subpopulations where a dual sample design was used, we did not include some sample cases in the denominator. Details are beyond the scope of this report but may be found in the User's Guide (Wright et al. 2017).

B. Response Rates

As indicated in Section A.2, the beneficiary population includes all SSI and/or SSDI beneficiaries aged 18 to FRA in active pay status as of June 30, 2014. In Table 2, we present the total number of beneficiaries sampled and the number of respondents, nonrespondents, and sample members who were ineligible due to death, incarceration, or other reasons, by stratum. In addition, we present the unweighted response rate and weighted response rates using the initial weight. The weighted response rates ranged from a low of 56.5 percent for 18- to 29-year-olds to a high of 65.5 percent for those 50 years old or older.

C. Methodology

The nonresponse bias analysis used data on individual members of the sampling frame and sample. The total number of beneficiaries in the target population (excluding U.S. territories) is 13,809,693, with some data missing for items of interest. The variables that we used (all categorical) follow:

1. Age category (4 levels).
   - 18-29
   - 30-39
   - 40-49
   - 50-FRA
2. Gender (2 levels).
   - Male
   - Female

3. Beneficiary type (3 levels).
   - SSI only
   - SSDI only
   - both SSI and SSDI
4. Race/ethnicity (6 levels).
   - Non-Hispanic White
   - Non-Hispanic Black
   - Non-Hispanic Asian
   - Non-Hispanic American Indian
   - Non-Hispanic Other
   - Hispanic
5. Constructed disability status (5 levels).
   - Hearing disability
   - Cognitive disability
   - Mental illness
   - Physical disability
   - Disability not given
6. Racial/ethnic characteristics of beneficiary's county (5 levels):
   - County with plurality or majority non–Hispanic Black population;
   - County with plurality or majority Hispanic population;
   - County with racially/ethnically mixed population, no majority group;
   - County with majority but less than 90 percent non–Hispanic White population;
   - County with at least 90 percent non–Hispanic White population
7. Economic characteristics of county (7 overlapping levels, each listed as binary variables):
   - Government-dependent economy county[11],
   - Service-dependent economy county[12],
   - Nonspecialized-dependent economy county[13],

[11] 15 percent or more of average annual labor and proprietors' earnings derived from Federal and State government during 1998-2000

[12] 45 percent or more of average annual labor and proprietors' earnings derived from services (SIC categories of retail trade; finance, insurance and real estate; and services) during 1998-2000

[13] County did not meet the dependence threshold for service, government, farming, mining, or manufacturing

- County with housing stress[14],
- County with low education[15],
- Population-loss county[16],
- Retirement-destination county[17]

8. Metropolitan status of county (6 levels):
   - Metropolitan area of 1 million population or more,
   - Metropolitan area of 250,000 to 999,999 population,
   - Metropolitan area of fewer than 250,000 population,
   - Nonmetropolitan area adjacent to large metropolitan area,
   - Nonmetropolitan area adjacent to medium or small metropolitan area,
   - Nonmetropolitan area not adjacent to metropolitan area.
9. Geographic region (U.S. Census Region) of beneficiary's residence (4 levels):
   - West
   - South
   - Northeast
   - Midwest.
10. Geographic region (U.S. Census Division) of beneficiary's residence (9 levels):
    - East North Central
    - West North Central
    - New England
    - Middle Atlantic
    - South Atlantic
    - East South Central
    - West South Central
    - Mountain
    - Pacific.

[14] 30 percent or more of households had one or more of these housing conditions in 2000: lacked complete plumbing, lacked complete kitchen, paid 30 percent or more of income for owner costs or rent, or had more than 1 person per room

[15] 25 percent or more of residents 25 through 64 years old had neither a high school diploma nor GED in 2000

[16] Number of residents declined both between the 1980 and 1990 censuses and between the 1990 and 2000 censuses

[17] Number of residents 60 and older grew by 15 percent or more between 1990 and 2000 due to immigration

11. Earnings category (5 levels):[18]
    - Three consecutive months of earnings above substantial gainful activity (SGA)[19] at some point in 2013 or 2014,
    - At least one month of earnings above $7,000 in 2013 or 2014,
    - At least one month of earnings above $2,000 in 2013 or 2014,
    - At least one month of earnings above $0 in 2013 or 2014,
    - No monthly earnings in 2013 or 2014.

After examining the extent of missing data for the above variables in the sampling frame (Table 3), we used the initial weights to compare the distributions of the variables across the frame, the total sample, and the sample split into two parts, the ineligibles and the remainder of the sample with ineligibles removed (Table 4). In Table 5, we compare the distributions of variables between the respondents (with ineligibles) and nonrespondents. We then compared the distributions among respondents with ineligibles using nonresponse-adjusted weights against the original sample with the original sample weights (Table 6).

In each table, we used SUDAAN to calculate standard errors in order to accommodate the sample design. The sample statistics consisted of proportions with an attribute (presented as percentages). We conducted comparisons for all beneficiaries. Several variables were missing values in the sample frame. In particular, in the beneficiary frame, race/ethnicity and disability type had missing values. In each case, the proportions with each attribute that were used in the following analyses were calculated among cases without missing data.

As is apparent from Table 3, the level of missingness for race/ethnicity is high, with approximately 12 percent of the frame males missing this variable. Any conclusions drawn from race/ethnicity therefore must be viewed with caution.

[18] We arrived at the five categories used for the earnings variable after a lengthy investigation using both (annual) IRS and (monthly) DCF earnings. Using data from the 2014 sampling frame, we calculated the percent with positive IRS earnings in 2014 (considered as "working"), as well as the mean and median IRS 2014 earnings, both overall and among those who were working. We compared these values to several sets of poststratified weights, where the poststratification was based on a variety of earnings categorical variables, each with different cutpoints, some with IRS earnings and some with DCF earnings. We determined that, although the IRS earnings are more accurate than DCF earnings, IRS earnings are only available annually, raising timing issues, and diluting the advantage of accuracy. It was also more difficult to use IRS earnings, since they could only be accessed by staff at SSA. We arrived at the cutpoints given above because these cutpoints resulted in a poststratified weights that resulted in estimated annual earnings that were closest to the IRS values.

[19] The monthly non-blind SGA earnings level was $1,040 in 2013 and $1,070 in 2014.

Table 3. Percentage of missing values for variables of interest

Variable	Weighted Percent Missing*				
	In Frame	In Entire Sample	Among Respondents	Among Nonrespondents	Among Ineligibles
Beneficiaries					
Race/ethnicity	12.0	11.5	11.6	11.6	10.1
Disability status	2.3	2.3	1.4	3.1	8.5

* The weights in the table are the initial base weights. All of the other variables did not have missing values in the sampling frame.

D. Results

In Table 4, we compare sample statistics of the variables for the entire sample of beneficiaries. The values are percentages for each level of the categorical variables, with the associated standard errors (se) in parentheses. The frame values do not have a standard error because they represent the original population and are without sampling error. Unknown categories are not included in the levels for these variables; proportions are calculated for the cases without missing data.[20] In the Tables 4 and 5, we applied initial weights to sample values for all columns except the frame percent, for which no weights were required (percentages calculated using the entire population).

We compare two types of variables. Greater emphasis was placed on the variables that are likely to be correlated with important outcome variables: beneficiary type, disability type, demographic variables, and the categorical earnings variable. Other variables are less likely to be highly correlated with outcome variables and thus receive less emphasis: geographic and economic characteristics associated with the beneficiary's county.

For each variable, approximate 95 percent confidence intervals can be created by adding and subtracting two standard errors from each point estimate among the sample values. We do not account for the fact that these "confidence intervals" are considered simultaneously, which would increase the Type I error (the probability that the confidence interval does not include the true value or the probability of rejecting the null hypothesis when it is true). Hence, one must consider this when significant results are observed.

[20] Values are assumed to be Missing Completely at Random (MCAR). While MCAR is normally a strong assumption, the level of missingness is so small for all but race/ethnicity that deviations from this assumption will not significantly change conclusions.

Table 4. Percentages with various attributes (categorical variables) using initial sampling weights

Variable	Frame Percent	Entire Sample Percent	(se)	Sample Percent, Known Ineligibles Removed	(se)	Ineligible Percent	(se)
Beneficiary Type							
SSI only	29.4	29.4	(0.8)	28.7	(0.8)	46.5	(4.6)*
SSDI only	56.1	55.8	(0.9)	56.2	(0.9)	47.3	(4.8)
Both SSI and SSDI	14.5	14.8	(0.6)	15.1	(0.6)	6.3	(1.8)*
Constructed Disability Status							
Hearing	0.7	0.7	(0.1)	0.7	(0.1)	0.1	(0.1)*
Cognitive	11.9	11.1	(0.5)	11.0	(0.5)	12.4	(3.0)
Mental	30.0	30.7	(0.8)	31.0	(0.9)	22.2	(3.6)*
Physical	57.4	57.5	(0.9)	57.2	(0.9)	65.3	(4.4)
Sex							
Male	50.9	50.1	(1.0)	49.7	(1.0)	60.1	(4.7)
Beneficiary's Age							
18–29 years	10.3	10.3	(0.3)	10.3	(0.3)	9.6	(1.3)
30–39 years	10.5	10.5	(0.3)	10.6	(0.3)	8.4	(1.2)
40–49 years	17.2	17.2	(0.5)	17.2	(0.5)	17.3	(2.3)
50–64 years	62.0	62.0	(0.8)	61.9	(0.8)	64.7	(3.6)
Race/Ethnicity							
White	66.5	68.5	(0.9)*	68.4	(0.9)	70.7	(4.4)
Black	22.8	22.6	(0.8)	22.7	(0.8)	21.1	(3.9)
Hispanic	4.2	3.8	(0.3)	3.8	(0.4)	3.8	(1.4)
All Others	6.5	5.1	(0.4)*	5.1	(0.4)*	4.4	(2.1)
County Racial/Ethnic Profile							
County with plurality or majority non-Hispanic black population	4.1	2.4	(0.3)*	2.3	(0.3)*	4.9	(2.0)
County with plurality or majority Hispanic population	9.5	8.5	(0.5)	8.6	(0.5)	6.0	(1.8)
County with majority but less than 90% non-Hispanic white population	37.9	45.1	(0.9)*	44.9	(1.0)*	50.1	(4.7)*
County with racially/ethnically mixed population, no majority group	34.1	33.3	(0.9)	33.3	(0.9)	31.6	(4.4)
County with at least 90% non-Hispanic white population	14.4	10.8	(0.6)*	10.9	(0.6)*	7.4	(2.3)*
Economic Characteristics of County							
Government-dependent economy county	11.9	11.7	(0.6)	11.7	(0.6)	12.9	(3.4)
Service-dependent economy county	37.9	39.9	(0.9)*	39.8	(0.9)*	41.9	(4.6)
Nonspecialized-dependent economy	24.3	26.2	(0.8)*	26.2	(0.9)*	27.4	(4.3)
County with housing stress	39.6	37.3	(0.9)*	37.4	(0.9)*	34.1	(4.3)
County with low education	15.2	11.4	(0.6)*	11.5	(0.6)*	9.4	(2.3)*
Population-loss county	11.6	5.2	(0.4)*	5.2	(0.4)*	5.2	(2.0)*
Retirement-destination county	12.8	14.9	(0.7)*	14.7	(0.7)*	18.4	(3.7)

TABLE 4 *(continued)*

Variable	Frame Percent	Entire Sample Percent (se)		Sample Percent, Known Ineligibles Removed (se)		Ineligible Percent (se)	
Metropolitan Status of County							
Metropolitan area of 1 million population or more	46.8	45.2	(0.9)	45.4	(1.0)	40.6	(4.6)
Metropolitan area of 250,000 to 999,999 population	22.3	26.0	(0.8)*	25.8	(0.9)*	29.8	(4.5)
Metropolitan area of fewer than 250,000 population	10.5	12.2	(0.6)*	12.2	(0.6)*	13.8	(3.3)
Nonmetropolitan area adjacent to large metropolitan area	4.4	3.9	(0.4)	4.0	(0.4)	2.6	(1.2)
Nonmetropolitan area adjacent to medium or small metropolitan area	9.1	9.1	(0.6)	9.1	(0.6)	7.5	(2.4)
Nonmetropolitan area not adjacent to metropolitan area	7.0	3.7	(0.4)*	3.6	(0.4)*	5.7	(2.3)
Census Region							
West	18.7	18.5	(0.7)	18.6	(0.8)	15.7	(3.2)
South	41.1	42.0	(0.9)	42.0	(1.0)	43.4	(4.7)
Northeast	18.4	18.3	(0.7)	18.2	(0.7)	20.7	(3.9)
Midwest	21.8	21.1	(0.8)	21.1	(0.8)	20.2	(3.8)
Census Division							
East North Central	15.6	15.1	(0.7)	15.2	(0.7)	12.2	(3.1)
West North Central	6.1	6.0	(0.4)	6.0	(0.4)	8.0	(2.7)
New England	5.0	4.7	(0.4)	4.6	(0.4)	7.5	(2.9)
Middle Atlantic	13.4	13.7	(0.6)	13.7	(0.6)	13.2	(3.0)
South Atlantic	20.1	19.6	(0.8)	19.5	(0.8)	22.9	(4.1)
East South Central	9.4	10.2	(0.6)	10.2	(0.6)	11.2	(2.9)
West South Central	11.7	12.2	(0.6)	12.3	(0.6)	9.3	(2.6)
Mountain	5.6	6.0	(0.5)	6.1	(0.5)	5.6	(2.2)
Pacific	13.1	12.5	(0.6)	12.6	(0.6)	10.1	(2.5)
Earnings Categories for 2013-2014 Time Period							
Three consecutive months of monthly earnings above SGA	0.8	0.8	(0.1)	0.7	(0.1)	1.3	(0.1)*
Monthly earnings above $7,000 in at least one month in ‘13 or ‘14	1.7	1.6	(0.2)	1.7	(0.2)	0.2	(0.2)*
Monthly earnings above $2,000 in at least one month in ’13 or ‘14	2.1	2.2	(0.2)	2.3	(0.2)	1.2	(0.8)
Monthly earnings above zero in at least one month in ’13 or ‘14	2.5	2.4	(0.2)	2.5	(0.2)	0.8	(0.3)*
Monthly earnings always zero in 2013 and 2014	92.8	93.0	(0.4)	92.9	(0.4)	96.5	(1.5)*

*Denotes a difference between the sample and frame value of more than two standard deviations.

1. Comparison of Entire Sample with Frame

Before conducting a nonresponse analysis, we must determine if the sample distribution adequately matches the frame distribution on important variables. This is necessary to ascertain whether the estimates using the sampling weights produce estimates that are consistent with population values. As shown in Table 4, the statistics estimated from the entire sample (using the initial sampling weight) among all beneficiaries are generally close to those computed with the full frame, although a few estimates—especially amongst the county-level variables defined from the AHRF—deviate from the frame value by more than two standard deviations. (Those varying by more than two standard deviations are denoted by *.)

Within PSUs, the samples were selected within explicit strata defined by age category, and implicit strata defined by disability status, gender, and race/ethnicity, in that priority order.[21] We would expect the distribution of all these variables to resemble the frame. However this is especially true for age category and the higher priority implicit stratification factors, and less so for the latter implicit stratification factors. Looking at Table 4, we see that this is generally true, though the sample had a significantly higher proportion of non-Hispanic Whites than the frame, and a significantly smaller proportion of "other races," which refers to Asians, American Indians, Alaska Natives, Native Hawaiians, other Pacific Islanders, or those of multiple races.[22] Since race/ethnicity is the lowest priority implicit stratification variable, this result is not surprising. Among other non–geography-based variables, no significant differences were found in the frame percentages and weighted sample percentages in the beneficiary sample. Larger differences are found with geographic county-level variables, including some levels of the racial/ethnic profile, economic characteristics, and metropolitan status of the sample member's county of residence. In particular, for the racial/ethnic profile variables relative to the sampling frame, the weighted sample estimates indicated fewer living in counties with a plurality or majority non-Hispanic black population, fewer living in counties with at least 90 percent white population, and more living in counties where whites were in the majority, but less than 90 percent.

For the economic characteristics variables relative to the sampling frame, the weighted sample estimates indicated more lived in counties that had service-dependent economies, and fewer lived in counties with nonspecialized economies, housing stress, population loss, and/or low education than the frame. Finally, the weighted sample estimates indicated a larger population living in counties that were part of metropolitan areas smaller than 1 million inhabitants and fewer living in nonmetropolitan counties than the frame.

[21] With explicit stratification, the population is subdivided into subpopulations (strata) defined by the levels of the explicit stratification variables, and independent samples are drawn from each strata, where the sampling fraction may or may not differ between strata. With this type of stratification, the size of the sample of each stratum is controlled. With implicit stratification, population members within each explicit stratum are sorted in priority order by the implicit stratification and the sample is selected using a sequential selection procedure. This imposes some, control on the distribution of these variables in the sample.

[22] These differences are only "just" significant, so this likely does not indicate a problem with the sample. The differences we are observing may be related to the missing data in the frame, as well as the fact that some significant results should be expected due to the fact that we are making several simultaneous comparisons without accounting for "multiple comparisons."

2. Removal of Ineligible Cases from Sample

If there are systematic differences between the estimates for the sampled eligible and ineligible cases, this could point to a problem in the frame, where the sample frame covers a different population than the target population. For example, if the sample frame consists of a large number of individuals that were found to be deceased due to a particular disability, the target population (as measured by the eligible sample) could have a smaller proportion with that disability than the sample frame. Approximately 3.9 percent of the beneficiary sample was found to be ineligible at data collection, representing about 4.0 percent of the population of SSI and SSDI beneficiaries on June 30, 2015. With this small percentage, it is unlikely that the population that includes ineligible cases will differ significantly from the population that does not. Nevertheless, it is instructive to investigate whether the population represented by eligible sample cases differs from the sample frame. There is some imprecision in this exercise, since the eligibility for the majority of nonrespondents is unknown. Therefore, some of the cases included in the column "sample cases with known ineligibles removed" will in fact be ineligible, because they were nonrespondents with unknown eligibility. For this exercise, we assume that the number of cases like this will be small. In Table 4, we have placed asterisks by the estimates from the sample with ineligible cases removed (using initial weights) that differ from the frame by more than two standard deviations. For these samples, it appears that the eligible sample does not differ markedly from the initial sample; the patterns of deviation from the frame that were observed in the initial sample are also observed with eligible cases. [23]

3. Assessment of Differences Between Respondents and Nonrespondents Before Nonresponse Adjustment

To avoid the issue of unknown ineligibles among nonrespondents, we look at the comparison between respondents and nonrespondents by including ineligibles among the respondents. These comparisons are shown in Table 5. Looking at general tendencies for the nongeographic variables in Table 4, beneficiary sample respondents and ineligibles were more likely than nonrespondents to (1) be female, (2) be older, and/or (3) have physical (non-hearing) disabilities. They were also less likely to be beneficiaries of SSI only. The race and earnings categories did not show any significant differences. Among the geographic variables, respondents/ineligibles were less likely than nonrespondents to come from metropolitan areas of one million or more, reside in counties with service-based economies and/or have a substantial portion of households in housing stress.[24] Finally, we observed regional differences. Respondents/ineligibles were less likely than nonrespondents to come from the West region and Pacific division and more likely to come from the Midwest region and the East North Central division. The intention of the nonresponse adjustments in the weights is to account for these differences. This is discussed in the next section.

[23] In other words, the pattern of asterisks between the "Entire Sample Percent (se)" column and the "Eligible Sample Percent (se)" column are nearly identical.

[24] The latter condition is defined as follows: 30 percent or more of households had one or more of these housing conditions in 2004: lacked complete plumbing, lacked complete kitchen, paid 30 percent or more of income for owner costs or rent, or had more than 1 person per room.

Table 5. Percentages with various attributes (categorical variables) using initial sampling weights among respondents (with ineligibles) and nonrespondents

Variable	Frame Percent	Entire Sample Percent	(se)	Respondents and Ineligibles Percent	(se)	Nonrespondent Percent	(se)	Difference	(t-statistic)
Beneficiary Type									
SSI only	29.4	29.4	(0.8)	27.9	(1.0)	32.0	(1.3)	-4.2	(-2.5)*
SSDI only	56.1	55.8	(0.9)	56.9	(1.2)	54.0	(1.4)	2.9	(1.6)
Both SSI and SSDI	14.5	14.8	(0.6)	15.2	(0.8)	14.0	(0.9)	1.3	(1.0)
Constructed Disability Status									
Hearing	0.7	0.7	(0.1)	0.4	(0.1)	1.2	(0.3)	-0.8	(-2.3)*
Cognitive	11.9	11.1	(0.5)	10.3	(0.6)	12.5	(0.8)	-2.2	(-2.3)*
Mental	30.0	30.7	(0.8)	29.4	(1.1)	32.9	(1.3)	-3.6	(-2.1)*
Physical	57.4	57.5	(0.9)	60.0	(1.2)	53.4	(1.4)	6.6	(3.5)*
Sex									
Male	50.9	50.1	(1.0)	48.4	(1.2)	53.1	(1.5)	-4.7	(-2.5)*
Beneficiary's Age									
18–29 years	10.3	10.3	(0.3)	9.3	(0.3)	11.9	(0.5)	-2.6	(-4.5)*
30–39 years	10.5	10.5	(0.3)	9.6	(0.4)	12.1	(0.5)	-2.5	(-4.1)*
40–49 years	17.2	17.2	(0.5)	16.2	(0.6)	18.8	(0.7)	-2.6	(-2.8)*
50–64 years	62.0	62.0	(0.8)	64.9	(0.9)	57.2	(1.3)	7.7	(4.9)*
Race/Ethnicity									
White	66.5	68.5	(0.9)	68.6	(1.2)	68.1	(1.4)	0.5	(0.3)
Black	22.8	22.6	(0.8)	22.6	(1.1)	22.7	(1.3)	-0.1	(-0.1)
Hispanic	4.2	3.8	(0.3)	4.0	(0.5)	3.6	(0.5)	0.4	(0.5)
All Others	6.5	5.1	(0.4)	4.8	(0.5)	5.5	(0.7)	-0.7	(-0.8)
County Racial/Ethnic Profile									
County with plurality or majority non-Hispanic black population	4.1	2.4	(0.3)	2.1	(0.3)	2.8	(0.5)	-0.7	(-1.2)
County with plurality or majority Hispanic population	9.5	8.5	(0.5)	7.6	(0.7)	9.8	(0.9)	-2.2	(-2.0)*
County with majority but less than 90% non-Hispanic white population	37.9	45.1	(0.9)	46.6	(1.2)	42.6	(1.4)	3.9	(2.1)*
County with racially/ethnically mixed population, no majority group	34.1	33.3	(0.9)	31.8	(1.1)	35.7	(1.4)	-3.9	(-2.1)*
County with at least 90% non-Hispanic white population	14.4	10.8	(0.6)	11.9	(0.8)	9.1	(0.8)	2.8	(2.4)*
Economic Characteristics of County									
Government-dependent economy county	11.9	11.7	(0.6)	11.3	(0.8)	12.5	(0.9)	-1.2	(1.0)
Service-dependent economy county	37.9	39.9	(0.9)	36.8	(1.2)	45.1	(1.4)	-8.2	(-4.4)*
Nonspecialized-dependent economy	24.3	26.2	(0.8)	28.0	(1.1)	23.2	(1.2)	4.8	(2.9)*
County with housing stress	39.6	37.3	(0.9)	33.6	(1.1)	43.5	(1.4)	-9.9	(-5.4)*
County with low education	15.2	11.4	(0.6)	10.7	(0.8)	12.7	(1.0)	-1.9	(-1.6)
Population-loss county	11.6	5.2	(0.4)	5.4	(0.6)	4.9	(0.6)	0.4	(0.5)
Retirement-destination county	12.8	14.9	(0.7)	15.3	(0.9)	14.1	(1.0)	1.2	(0.9)

TABLE 5 *(continued)*

Variable	Frame Percent	Entire Sample Percent	(se)	Respondents and Ineligibles Percent	(se)	Nonrespondent Percent	(se)	Difference	(t-statistic)
Metropolitan Status of County									
Metropolitan area of 1 million population or more	46.8	45.2	(0.9)	42.0	(1.2)	50.5	(1.5)	-8.5	(-4.5)*
Metropolitan area of 250,000 to 999,999 population	22.3	26.0	(0.8)	26.9	(1.1)	24.3	(1.2)	2.6	(1.5)
Metropolitan area of fewer than 250,000 population	10.5	12.2	(0.6)	12.8	(0.8)	11.4	(0.9)	1.4	(1.1)
Nonmetropolitan area adjacent to large metropolitan area	4.4	3.9	(0.4)	4.4	(0.5)	3.0	(0.5)	1.4	(1.9)
Nonmetropolitan area adjacent to medium or small metropolitan area	9.1	9.1	(0.6)	9.8	(0.8)	7.7	(0.8)	2.1	(1.8)
Nonmetropolitan area not adjacent to metropolitan area	7.0	3.7	(0.4)	4.1	(0.5)	3.0	(0.5)	1.1	(1.4)
Census Region									
West	18.7	18.5	(0.7)	16.8	(0.9)	21.4	(1.2)	-4.6	(-3.1)*
South	41.1	42.0	(0.9)	42.2	(1.2)	41.7	(1.4)	0.5	(0.3)
Northeast	18.4	18.3	(0.7)	17.5	(0.9)	19.8	(1.1)	-2.3	(-1.6)
Midwest	21.8	21.1	(0.8)	23.5	(1.1)	17.1	(1.1)	6.4	(4.2)*
Census Division									
East North Central	15.6	15.1	(0.7)	17.0	(1.0)	11.8	(0.9)	5.2	(3.9)*
West North Central	6.1	6.0	(0.4)	6.5	(0.6)	5.3	(0.6)	1.2	(1.4)
New England	5.0	4.7	(0.4)	4.5	(0.5)	4.9	(0.6)	-0.4	(-0.5)
Middle Atlantic	13.4	13.7	(0.6)	12.9	(0.8)	14.8	(1.0)	-1.9	(-1.5)
South Atlantic	20.1	19.6	(0.8)	19.9	(1.0)	19.2	(1.2)	0.7	(0.5)
East South Central	9.4	10.2	(0.6)	10.4	(0.7)	9.9	(0.9)	0.6	(0.5)
West South Central	11.7	12.2	(0.6)	11.9	(0.8)	12.7	(1.0)	-0.8	(-0.6)
Mountain	5.6	6.0	(0.5)	6.4	(0.7)	5.5	(0.7)	0.9	(0.9)
Pacific	13.1	12.5	(0.6)	10.4	(0.7)	15.9	(1.0)*	-5.5	(-4.3)*
Earnings Categories for 2013-2014 Time Period									
Three consecutive months of monthly earnings above SGA	0.8	0.8	(0.1)	0.6	(0.1)	1.0	(0.2)	-0.4	(-1.5)
Monthly earnings above $7,000 in at least one month in '13 or '14	1.7	1.6	(0.2)	1.6	(0.3)	1.7	(0.2)	-0.1	(-0.3)
Monthly earnings above $2,000 in at least one month in '13 or '14	2.1	2.2	(0.2)	2.2	(0.3)	2.2	(0.3)	0.1	(0.2)
Monthly earnings above zero in at least one month in '13 or '14	2.5	2.4	(0.2)	2.5	(0.3)	2.2	(0.2)	0.3	(0.8)
Monthly earnings always zero in 2013 and 2014	92.8	93.0	(0.4)	93.0	(0.5)	92.9	(0.5)	0.1	(0.2)

*Denotes a difference between the sample and frame value of more than two standard deviations.

4. Nonresponse Adjustment

Nonresponse adjustments seek to reduce the potential for bias that might result from differential nonresponse on the basis of the variables used in the nonresponse adjustment. We calculated two separate nonresponse adjustments using a logistic propensity model for location and another logistic propensity model for cooperation. The predicted value from the model was the probability that a sample member was either located or responded to the survey. We used a Chi-square Automatic Interaction Detector (CHAID) analysis in SPSS to identify possible statistically significant interactions.[25] If an interaction was included in a candidate model, then the main effects associated with that interaction were also always included. At a particular level of a given covariate or interaction, if all respondents either were located or unlocated (for the location models), complete or not complete (for the cooperation models), or the total number of sample members at that level was fewer than 20, we combined levels if combining of levels was possible or logical. If combining levels was not possible, we excluded the covariate or interaction from the pool.

We used forward and backward stepwise selection logistic regression procedures using normalized weights to reduce the pool of covariates, which included both main effects and the interactions from CHAID.[26] Next, we carefully evaluated a series of models by comparing the following measures of predictive ability and goodness of fit: the Generalized Coefficient of Determination (also known as the Generalized R-squared statistic),[27] Akaike's Information Criterion (AIC),[28] percentage of concordant and discordant pairs,[29] and the Hosmer-Lemeshow

[25] CHAID normally is attributed to Kass (1980) and Biggs et al. (1991), and its application in SPSS is described in Magidson (1993). The CHAID procedure iteratively segments a data set into mutually exclusive subgroups that share similar characteristics based on their effect on nominal or ordinal dependent variables. It automatically checks all variables in the data set and creates a hierarchy that shows all statistically significant subgroups. The procedure generates a tree that identifies the set of variables and interactions among the variables that have an association with the ability to locate a sample member (and the propensity of a located sample member to respond or be ineligible). We first ran CHAID with all covariates and then re-ran it a few times with the top variable in the tree removed in order to ensure that all potentially important interactions were retained for further consideration.

[26] The stepwise logistic regression procedure does not take into account the sampling design when computing standard errors so the variances are usually under-estimated. The final model is developed using SUDAAN to incorporate the sample design features of stratification and clustering.

[27] The Generalized Coefficient of Determination (Cox and Snell 1989) is a measure of the adequacy of the model, where higher numbers indicate a greater difference between the likelihood of the model in question and the likelihood of the null model. The Max rescaled R-Square scales this value to have a maximum of 1.

[28] Akaike's Information Criterion (AIC) is defined as AIC = -2LogL + 2(k+s), where LogL is the log-likelihood of the binomial distribution using the parameters from the given model, k is the total number of response levels minus one, and s is the number of explanatory effects (Akaike 1974). AIC is a relative number and has no meaning on its own. For a given model, smaller values of AIC are preferable to larger values.

[29] A pair of observations is concordant if a responding subject has a higher predicted value than the nonresponding subject, discordant if not, and tied if both members of the pair are either respondents, nonrespondents, or have the same predicted values. The "predicted value" is the probability of location or response from the logistic propensity model. It is desirable to have as many concordant and as few discordant pairs as possible (Agresti 1990).

goodness-of-fit test.[30] The selection of the final model involved evaluating these measures in concert, choosing a parsimonious model that was among the best in all of these measures using SUDAAN. Model fitting also involved a review of the statistical significance of the coefficients of the covariates in the model and avoidance of any unusually large adjustment factors. In addition, we manipulated the set of variables to avoid data warnings in SUDAAN.[31] Once we finalized the model, we calculated the location and cooperation adjustments as the inverse of the propensity scores. We then trimmed the nonresponse-adjusted weights (if necessary) to reduce the variance attributable to outlier weights.[32] Finally, we post-stratified the weights so that the weighted totals for beneficiary type, age category, gender, and earnings category added up to frame totals. When applying the nonresponse-adjusted weights to counts of these variables, we observed that they did not match the frame exactly because the post-stratification included ineligible cases, which were removed from these counts. The counts should, however, be close.

5. Comparison of Respondents to Original Sample after Nonresponse Adjustment

In this analysis, we have included some variables that were not included in the nonresponse adjustment process. For example, we did not include beneficiary type in the nonresponse adjustments and included only some levels of race/ethnicity, disability type, and the geography-based variables. However, the adjustments included the number of addresses and phone numbers on SSA files for each beneficiary, and information about the relationship between the payee and the beneficiary.

In Table 6, we include percentages from the sample frame, estimates from the entire sample (using initial sampling weights), and nonresponse-adjusted weighted estimates among respondents and ineligibles (again, including ineligibles because the number of ineligibles among nonrespondents is unknown). Ideally, we would like to make comparisons between nonresponse-adjusted weighted estimates and percentages from the sample frame. However, there are differences between the sample and the frame, particularly among the geographic-based variables, that are due to the fact that the sample design did not control for these variables. To ensure we are limiting our attention to differences due to nonresponse, we make comparisons between the nonresponse-adjusted weighted estimates and the estimates from the entire sample (using initial sampling weights). Estimating the standard errors for these differences is problematic, since the two groups are not independent. However, for this exercise, we treat the estimates from the entire sample as “truth” (without standard errors), and use the standard errors

[30] The Hosmer-Lemeshow Goodness-of-Fit Test is a test for goodness of fit of logistic regression models. Unlike the Pearson and deviance goodness-of-fit tests, it may be used to test goodness of fit even when some covariates are continuous (Hosmer and Lemeshow 1989).

[31] SUDAAN data warnings usually included one or more of the following: (1) an indication of a response cell with zero count; (2) one or more parameters approaching infinity (which may not be readily observable with the parameter estimates themselves); and (3) degrees of freedom for overall contrast less than the maximum number of estimable parameters. We tried to avoid all such warnings, although avoiding the first two was of highest priority. The warnings almost always were caused by a response cell with a count that was too small, which required dropping the covariate or combining categories of a covariate.

[32] Trimming is a process whereby outlier weights are trimmed to be closer to the rest of the weights in distribution. The trimmed amount is reallocated to the rest of the weights in the sample. The decision about how much to trim is a subjective one, and is based on the balance between reducing the variance in the weights, and minimizing any increase in bias that might result from trimming.

from the nonresponse-adjusted weighted estimates. Note that we poststratified the counts to match the frame for beneficiary type, age, and the earnings categories.

As Table 6 indicates, the nonresponse-adjusted weighted estimate for respondents is generally close to the initial-weighted estimates for the entire sample (and the population). The nonresponse adjustments alleviated all of the differences observed between respondents and nonrespondents, as nearly all the nonresponse-adjusted weighted estimates are within two standard deviations of the weighted estimates using the initial sampling weights. The only exception is Hispanic, where the nonresponse-adjusted weighted estimate is 4.0 percent, and the weighted estimate using the initial sampling weights is 3.8 percent. Notice that the nonresponse-adjusted weighted estimate is actually closer to the value from the sampling frame (4.2 percent).

Table 6. Percentages with various attributes (categorical variables) comparing frame percent with final weighted estimate (using nonresponse-adjusted weights), beneficiaries

Variable	Frame Percent	Entire Sample Percent Using Initial Weights	(se)	Respondents/ Ineligibles with Attribute	Respondents Weighted Percent Using Adjusted Weights	(se)
Beneficiary Type						
SSI only	29.4	29.4	(0.8)	1,749	29.4	(1.0)
SSDI only	56.1	55.8	(0.9)	1,748	56.1	(1.2)
Both SSI and SSDI	14.5	14.8	(0.6)	862	14.5	(0.8)
Constructed Disability Status						
Hearing	0.7	0.7	(0.1)	44	0.6	(0.1)
Cognitive	11.9	11.1	(0.5)	867	11.1	(0.6)
Mental	30.0	30.7	(0.8)	1,574	30.2	(1.1)
Physical	57.4	57.5	(0.9)	1,798	58.1	(1.2)
Sex						
Male	50.9	50.1	(0.9)	2,247	50.9	(1.2)
Beneficiary's Age						
18–29 years	10.3	10.3	(0.3)	1,240	10.3	(0.4)
30–39 years	10.5	10.5	(0.3)	1,168	10.5	(0.4)
40–49 years	17.2	17.2	(0.5)	1,186	17.2	(0.6)
50–64 years	62.0	62.0	(0.8)	765	62.0	(1.0)
Race/Ethnicity						
White	66.5	68.5	(0.9)	2,225	68.1	(1.2)
Black	22.8	22.6	(0.8)	949	22.9	(1.0)
Hispanic	4.2	3.8	(0.3)	213	4.0	(0.5)*
All Others	6.5	5.1	(0.4)	206	4.9	(0.5)
County Racial/Ethnic Profile						
County with plurality or majority non-Hispanic black population	4.1	2.4	(0.3)	108	2.2	(0.3)
County with plurality or majority Hispanic population	9.5	8.4	(0.5)	358	8.2	(0.7)
County with majority but less than 90% non-Hispanic white population	37.9	45.1	(0.9)	2,002	45.8	(1.2)
County with racially/ethnically mixed population, no majority group	34.1	33.2	(0.9)	1,438	32.9	(1.1)
County with at least 90% non-Hispanic white population	14.4	10.8	(0.6)	453	10.9	(0.8)
Economic Characteristics of County						
Government-dependent economy county	11.9	11.7	(0.6)	481	11.6	(0.8)
Service-dependent economy county	37.9	39.9	(0.9)	1,742	39.8	(1.2)
Nonspecialized-dependent economy	24.3	26.2	(0.8)	1,176	26.0	(1.0)
County with housing stress	39.6	37.3	(0.9)	1,616	36.3	(1.2)
County with low education	15.2	11.4	(0.6)	490	11.1	(0.8)
Population-loss county	11.6	5.2	(0.4)	221	5.3	(0.5)
Retirement-destination county	12.8	14.8	(0.7)	665	15.2	(0.9)

TABLE 6 (*continued*)

Variable	Frame Percent	Entire Sample Percent Using Initial Weights (se)		Respondents/ Ineligibles with Attribute	Respondents Weighted Percent Using Adjusted Weights (se)	
Metropolitan Status of County						
Metropolitan area of 1 million population or more	46.8	45.2	(0.9)	1,963	45.2	(1.2)
Metropolitan area of 250,000 to 999,999 population	22.3	26.0	(0.8)	1,173	25.6	(1.1)
Metropolitan area of fewer than 250,000 population	10.5	12.2	(0.6)	549	12.4	(0.8)
Nonmetropolitan area adjacent to large metropolitan area	4.4	3.9	(0.4)	162	3.9	(0.4)
Nonmetropolitan area adjacent to medium or small metropolitan area	9.1	9.1	(0.6)	362	9.0	(0.7)
Nonmetropolitan area not adjacent to metropolitan area	7.0	3.7	(0.4)	150	3.8	(0.5)
Census Region						
West	18.7	18.5	(0.7)	759	18.0	(0.9)
South	41.1	42.0	(0.9)	1,820	41.6	(1.2)
Northeast	18.4	18.3	(0.7)	814	18.0	(0.9)
Midwest	21.8	21.1	(0.8)	966	22.4	(1.0)
Census Division						
East North Central	15.6	15.1	(0.7)	657	16.4	(0.9)
West North Central	6.1	6.0	(0.4)	309	6.1	(0.5)
New England	5.0	4.7	(0.4)	218	4.6	(0.5)
Middle Atlantic	13.4	13.7	(0.6)	596	13.3	(0.8)
South Atlantic	20.1	19.6	(0.8)	840	19.4	(0.9)
East South Central	9.4	10.2	(0.6)	436	10.2	(0.7)
West South Central	11.7	12.2	(0.6)	544	12.0	(0.8)
Mountain	5.6	6.0	(0.5)	258	6.3	(0.6)
Pacific	13.1	12.5	(0.6)	501	11.7	(0.8)
Earnings Categories for 2013-2014 Time Period						
Three consecutive months of monthly earnings above SGA	0.8	0.8	(0.1)	49	0.8	(0.2)
Monthly earnings above $7,000 in at least one month in ’13 or ‘14	1.7	1.6	(0.2)	96	1.7	(0.3)
Monthly earnings above $2,000 in at least one month in ’13 or ‘14	2.1	2.2	(0.2)	158	2.1	(0.3)
Monthly earnings above zero in at least one month in ’13 or ‘14	2.5	2.4	(0.2)	195	2.5	(0.3)
Monthly earnings always zero in 2013 and 2014	92.8	93.0	(0.4)	3,861	92.8	(0.5)

* Denotes a difference between the sample and frame value of more than two standard deviations.

E. Summary and Implications for Analyses

In this analysis, we have shown that, despite a few minor differences between the sample frame and the weighted estimates from the sample using initial weights, the selected sample was representative of the population of interest among variables used for either explicit or implicit stratification. There were differences between the sample and the frame for other variables, particularly for race, county ethnic profile, county economic profile, and metropolitan status. Because we did not achieve an 80-percent response rate, the main purpose of this nonresponse bias analysis was to determine if systematic differences between respondents and nonrespondents were alleviated by nonresponse adjustments to the weights, or if the potential for nonresponse bias still existed in weighted estimates.

We found that the nonresponse adjustment alleviated nearly all differences observed between respondents and nonrespondents in the beneficiary sample. Due to the differences between the sample and the frame, we decided to make comparisons between the nonresponse-adjusted weighted estimates and the entire sample estimates using the initial sampling weights. The only noted difference between the nonresponse-adjusted weighted estimates and the entire sample estimates was the proportion Hispanic, where the nonresponse-adjusted weighted estimate was actually closer to the frame value than the estimate from the entire sample using initial sampling weights. Any differences that existed between the nonresponse-adjusted weighted estimates and the sampling frame also existed between the entire sample using initial sampling weights and the sampling frame, and were not due to nonresponse.

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