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MEMORANDUM FOR Jason Fields
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From: Ruth Ann Killion*(Signed)*
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Subject: Nonresponse Bias Analysis for Wave 1 2008 Survey of Income and Program Participation (SIPP) (ALYS-12)

This document describes the results of the nonresponse bias analysis for Wave 1 of the 2008 Survey of Income and Program Participation (SIPP).

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Nonresponse Bias Analysis for Wave 1 of the 2008 Survey of Income and Program Participation (SIPP)

By Sarah McMillan and Ralph Culver III

2013

1 Introduction

For a household survey, unit nonresponse is the failure to obtain any survey measures on a sample unit (e.g. household). These nonresponse rates have been increasing in recent years, even for the large government surveys. With this increasing nonresponse there is also growing concern over data quality and losing valuable information from these nonrespondents. Declining response rates can be an indicator of nonresponse bias, or a difference in survey measures between respondents and nonrespondents, which can affect data quality. However, there is not always a direct link between response rates and nonresponse, since "nonresponse bias can vary across different statistics in the same survey; thus, low response rate surveys are not necessarily "bad" per se, but they may yield some statistics subject to large nonresponse bias" [2]. Therefore, understanding and measuring nonresponse bias for our key estimates is an important aspect in determining overall data quality.

Because policy makers use estimates from the demographic surveys conducted by the U.S. Census Bureau and other agencies to determine the successfulness of programs or for national economic indicators, the highest data quality is a necessity. This has led more surveys to investigate nonresponse bias, especially after the Office of Management and Budget (OMB) released their standards in 2006 that require survey programs to make plans for a nonresponse bias analysis if unit response rates fall below 80% [5, pg. 8 Guideline 1.3.4]. The Census Bureau incorporated this guideline into its own standards along with guidelines directed at cumulative response rates and sample attrition specific to longitudinal surveys. These guidelines state that serious data quality issues related to nonsampling error can occur when cumulative response rates for a longitudinal survey fall below 60% and when sample attrition from wave to wave are greater than 5% [11, pg. 114 Requirement F1-6].

The purpose of this report is to document the findings for the first stage of a nonresponse bias analysis for the Survey of Income and Program Participation (SIPP). The SIPP is a longitudinal survey that collects detailed information about income, employment, health insurance, and participation in government programs. It is administered in panels that last three to four years with interviews being conducted at 4-month intervals called waves. The SIPP has a complex sample design with about 65,000 households in sample for the first interview. The most recent SIPP panel started in September 2008 with an initial weighted response rate of 80.6%. Previous panels had higher overall response rates around 85-90% [8, 9]. This slight decrease alone was not a cause of concern, but with later wave response rates dropping below 80% and the sample loss rate, which is an estimate of sample attrition, in later waves nearing 40%, we decided to assess possible data quality issues in the SIPP by conducting a nonresponse bias analysis.

This report focuses on the Wave 1 nonresponse, since this is when the greatest proportion of nonresponse occurs. We will use several of the tools listed in a course given by the Joint Program in Survey Methodology through the University of Michigan called "Practical Tools for Nonresponse Bias Studies" including benchmarking, comparing response rates across subgroups, comparing frame characteristics for the full sample and respondents, and examining logistic regressions on an indicator of response. Future work will include an in-depth analysis of later waves' nonresponse, as well as, taking a look at the longitudinal aspect of nonresponse.

2 Data and Methods

Data

The 2008 Panel of the Survey of Income and Program Participation was used as the data for this analysis. The SIPP is designed to collect detailed information on income, employment, health insurance, and program eligibility and participation for the civilian noninstitutionalized population living in the United States. According to the SIPP Source and Accuracy Statement for 2008, a systematic selection was used to select housing units within 351 primary sampling units (PSUs) from the master address file created from the 2000 Decennial Census. In addition, households located in areas with a higher concentration of low-income households were oversampled by 44 percent to increase the accuracy of estimates for statistics of low-income households and program participation [13].

When a respondent is interviewed, data is collected about the four preceding months. These four reference months comprise one wave. Only data from Wave 1, which covered the reference period from May 2008 to November 2008[1], was included in this first analysis. The sample in Wave 1 consisted of approximately 65,500 households of which only 53,031 of the households were eligible for interview. Of those eligible households, 42,032 were interviewed, with a weighted response rate of 80.6% [13]. In subsequent waves, all adults who were interviewed in Wave 1 were followed and interviews were attempted for all household members. The majority of unit nonresponse occurs in Wave 1, so this was our initial focus for studying nonresponse bias. Frame variables available for both respondents and nonrespondents are only available for a subgroup of households having data from the 2000 Decennial Census. Therefore, only this subgroup was included in these analyses.

Because SIPP is longitudinal, these response rates do not give us the complete picture of nonresponse, we must also look at the total sample attrition. The SIPP measures sample attrition using a sample loss rate. It is calculated by taking into account the Wave 1 nonresponse and each subsequent wave's nonresponse. Given that SIPP interviews new household members joining the household after Wave 1, the growth of nonresponding households is estimated and included in the sample loss rate. For the 2008 SIPP Panel, sample attrition between waves was largest from Wave 1 to Wave 2 at 6.6%. The sample loss rate for this panel was largest at Wave 1 at 19.2% and, is currently, 39.8% for Wave 9 [13]. More attention will be given to later wave attrition in future analyses.

Analytic Variables

Actual estimates of nonresponse bias can only be produced for variables that are known for both respondents and nonrespondents. We only have this information for our frame variables, so we must calculate nonresponse bias on these variables and make interpretations about our interest variables. The limited number of variables contained on the frame were collected from the 2000 Decennial Census long and short forms, but are known for both respondents and nonrespondents. This included the following variables

[1] The SIPP sample is divided into four equal groups, called rotation groups. A new rotation group is interviewed each month and asked about the four preceding months. Rotation group 1 of Wave 1 was interviewed in September 2008 and asked about May, June, July, and August. Rotation group 2 was interviewed in October 2008 and asked about June, July, August, and September. Rotation group 3 was interviewed in November 2008 and asked about July-October and rotation group 4 was interviewed in December and asked about August-November.

- *Age of Householder*
- *Gender of Householder*
- *Number of Household Members*
- *Race of Householder* (Two levels: Black, Non-Black)
- *Tenure* (Two levels: Renter, Owner)
- *Urban/Rural* (Two levels: Urban area, Rural area)
- *Region* (Four levels: Northeast, South, Midwest, West)
- *CBSA area* (Three levels: In Principal City of Metropolitan Statistical Area (MSA), In MSA not in Principal City, Not in MSA or Principal city)
- *Within PSU Strata* (Two levels: Low Income household, Non-low Income) This variable was based on a probability calculated using 2000 Census Long Form income data within a designated geographic region and was used for determining

Because nonresponse bias is specific to a statistic, we can only identify potential statistics subject to bias using variables from the frame that are correlated to our key estimates. We would like to measure the nonresponse bias associated with some of SIPP's key estimates including total participants of Medicare, Medicaid, Supplemental Nutrition and Assistance Program (SNAP), Social Security, and Supplemental Security Income (SSI).

Previous Research

Previous efforts to examine the bias and determine the impact on SIPP estimates included a variety of different studies. Certain demographic subgroups are underrepresented in the SIPP due to undercoverage and nonresponse. These include young black males, Hispanic males, metropolitan residents, renters, movers, and those that have been divorced, widowed or are separated [10, pg 6-5]. A study of the 1984 panel by McArthur, compared characteristics of persons that responded for 9 waves to those that had one of more noninterviews. Her results indicated that renters, members of racial minorities, individuals aged 15-24, individuals that were never married, and individuals without a savings account or other assets were more likely to be nonrespondents [9, pg 51].

A comparison between SIPP estimates for the 1990 and 1984 panels with comparable CPS estimates showed that SIPP estimates were lower on most types of income [9, pg. 124-129]. However, for transfer payment programs like Social Security, Railroad retirement, and SSI estimates of income from SIPP were closer to estimates from program sources than CPS. SIPP estimates of Social Security income amounted to 98% of the program total, Railroad retirement income amounted to 96%, and SSI was 95% of the total from administrative records. However, SIPP estimates of public assistance income, including Aid to Families with Dependent Children (AFDC), were much lower compared to the program sources. SIPP and CPS estimates of income from AFDC only amounted to 72% of the program total [9, pg 130-132].

Mack and Petroni [4] summarize the results from several studies that looked into using logistic regression and various raking methodologies for nonresponse weighting adjustments. The results indicated that alternative weighting procedures did not reduce the bias more than the current adjustment for estimates of income, unemployment, government assistance and poverty.

Statistical Analysis

This analysis involved using four different techniques for studying the magnitude and direction of nonresponse bias. These studies included a benchmark analysis, comparison of response rates across various subgroups, comparison of frame characteristics for respondents and nonrespondents, and a logistic regression to examine effects of characteristics on nonresponse. Further analysis will include comparing characteristics of later wave respondents and nonrespondents, and calculation of the representivity of the survey, as indicated by an R indicator.

Benchmarking, or comparing the magnitude of survey estimates to an independent source, is a useful beginning tool to determine possible bias. Administrative records are a good independent source to represent the "gold standard" as they are the result of complete records and not results from a survey. For our study, the "gold standard" was official counts from the Center for Medicare and Medicaid Services, United States Agriculture Department (SNAP), and the Social Security Administration (SSI and SS). These counts were compared to similar estimates from the SIPP and depending on the available estimates, were broken into categories. For calculating totals, we used SAS PROC SURVEYMEANS and incorporated the final weights that are adjusted for nonresponse and raked to Census controls. Then statistical testing using generalized variance parameters were used to test for significant differences. These comparisons gave us an idea of which statistics could have potential bias. The weakness of this tool is that all data sources are subject to error, so even the "gold standard" has some degree of error that confounds an estimate of nonresponse bias. Additionally, we can have other errors in our survey estimate besides nonresponse bias.

The remaining analyses involve using data from the frame. The Census 2000 Address Files were used to select approximately 80% of the SIPP 2008 sample. Using data from the frame allowed us to find areas of potential nonresponse bias for statistics based on the frame variables that, in turn, gave us some insight into the bias of the correlated key estimates. By first using PROC CORR, we determined the correlation coefficients of our frame variables with our key estimates of Medicare, Medicaid, SNAP, Supplemental Security Insurance, or Social Security. Only the Within PSU Stratum variable had a correlation of greater than 0.2[2]. All other frame variables had correlations below 0.05.

The first analysis using the frame data involved calculating weighted unit response rates for various subgroups of the population. Response rates were calculated according to the Census Bureau Quality Standards D3-A [11] using the base weight and the MEAN statement with the SVY command to adjust for stratification and clustering in STATA 12. The base weight is the inverse of the probability of selection and does not contain any adjustments for nonresponse. Highly variable response rates among the subgroups indicate a potential for nonresponse bias for that estimate. Subgroups with lower response rates relative to the other subgroups can indicate that particular subgroup is underrepresented in the final sample. Similarly, the subgroups with higher response rates indicate the particular subgroup is overrepresented in the final sample [5]. The LINCOM command in STATA was used to test for significant differences in the response rates among the groups. The weakness of this approach is we are only finding areas of potential

[2] Within PSU Stratum is the variable used to distinguish between the oversample and nonoversample strata.

bias for frame variables and a direct estimate of the bias cannot be obtained. Also since we are using the base weight we do not know if these potential biases are accounted for in the nonresponse adjustment. The next analysis tried to examine this aspect.

The next study involved comparing weighted percentages of the frame variables for the full sample and then for the respondents using both the base weight and the nonresponse adjusted weight. Estimates were calculated using MEAN and TABULATE commands in STATA 12 with the appropriate adjustments for the complex sample design and using the sample base weight. The difference between the full-sample statistic and the respondent statistic will be an estimate of nonresponse bias for the frame variable. Additionally, the difference between the respondent statistic using the base weight compared to the statistic using the nonresponse adjusted weight will give us an idea of whether the nonresponse adjustment resulted in a reduction in the bias. To test for significant differences between the statistics, we the LINCOM command in STATA. The weakness of this approach is that we can only estimate nonresponse bias for the estimates of frame variables, not our actual key estimates. If these are correlated, then it can give us insight into areas of potential bias associated with our key estimates.

For the final study, we modeled a dependent variable that was a binary indicator of response using a logistic regression. The model used in PROC SURVEYLOGISTIC is a linear logistic model with the form $logit\,(\pi) = \log\left(\frac{\pi}{1-\pi}\right) = \alpha + \boldsymbol{x\beta}$ where $\boldsymbol{x}$ is a row vector, π is the response probability to be modeled, α is the intercept parameter, and $\boldsymbol{\beta}$ is the vector of slope parameters. Therefore, we have $\boldsymbol{x\beta} = \beta_0 + \beta_1 x_1 + \cdots + \beta_k x_k$ for k independent variables. Each frame variable served as one of the independent variables. Using PROC SURVEYLOGISTIC, with adjustments for sample design and using the base weight, we preformed a stepwise weighted regression to estimate coefficients, standard errors, and odds ratios. This tool tells us which groups had a higher propensity to respond. In a future analysis, we will divide these response propensities into groups to calculate means of respondent information to compare across groups to indicate potential bias. Additionally, we can calculate the standard deviation of the response probabilities to get a Representativity Indicator (R-indicator). The R-indicator is an overall measure that measures the difference between respondents and non-respondents and it measures how the respondents resemble the population.

3 Results

Tables 1 through 4 summarize the results of our Benchmark study. We compare estimates of total participation in the Supplemental Nutrition Assistance Program (SNAP), Social Security, Supplemental Security Income (SSI), Medicaid, and Medicare obtained from SIPP data to totals obtained from the program sources (i.e. our benchmark). Each table includes a SIPP estimate, the benchmark, the difference between the two totals (Benchmark – SIPP) and the ratio of the SIPP estimate to the Benchmark. Comparisons were tested using generalized variance parameters and all significant differences are highlighted.

Table 1 compares overall participation rates for each of the programs considered. These results indicate that SIPP is underestimating participation in the specified government programs. The largest differences are seen for Medicare and Medicaid, where the SIPP estimates are only about

75% of the program totals[3]. The SIPP is better at estimating participation in SNAP, Social Security, and SSI, with the SIPP estimate being about 84% of the program total for SNAP and about 90% of the program total for Social Security and SSI.

Table 1 – Comparison of Overall Total Participation Rates

	SIPP Estimate	SIPP 90% Confidence Interval	Benchmark Total	Difference	Ratio
SNAP	24,521,852	(24,049,590, 24,994,114)	29,216,546[2]	4,694,694*	84%
Social Security	45,733,625	(45,114,067, 46,353,183)	50,898,244[3]	5,164,619*	90%
Supplemental Security Income (SSI)	6,821,343	(6,564,365, 7,078,321)	7,468,701[4]	647,358*	91%
Medicaid	42,407,921	(41,807,416, 43,008,426)	58,771,000[5]	16,363,079*	72%
Medicare	41,006,104	(40,413,999, 41,598,209)	55,220,000[6]	14,213,896*	74%

* indicates difference is statistically significant at the 10% significance level.

[1] The total participation was sent via email by a program analyst from the U.S. Department of Agriculture, Food and Nutrition Service.

[2] The Social Security totals are a combination of participants in Old-Age and Survivors Insurance (OASI), Trust Fund and the Disability Insurance (DI) Trust Fund. The total for Social Security is from December 2008. http://www.ssa.gov/policy/docs/statcomps/supplement/2009/5a.html#table5 (Tables 5.A1)

[3] http://www.ssa.gov/policy/docs/statcomps/ssi_monthly/2008/table02.pdf

[4] The total for Medicaid is from fiscal year 2008. http://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/MedicareMedicaidStatSupp/2010.html (Table 13.4)

[5] The total for Medicare is from calendar year 2008. https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/ReportsTrustFunds/Downloads/TR2009.pdf (Table III.A3)

We then broke down these total participation rates into different categories and present them in Tables 2-4. We've included age breakdowns for social security and SSI and state estimates for SNAP. Breakdowns for Medicare and Medicaid were not available.

Table 2 breaks down Social Security participation rates by age. SIPP does well at estimating the total number of participants aged 62 and older, accounting for 94% of the Social Security total. However, for those less than 62 SIPP only accounts for 76% of the Social Security total. One reason for underestimating Social Security is respondents may be confused between Social Security and SSI. The less than 62 age group can only receive Social Security payments if they are determined to be unable to work. SSI payments are given if a person has low-income, blind or disabled.

[3] The differences between the SIPP estimates and the benchmarks for SNAP and for Social Security are not statistically significant at the 10% significance level.

Table 2 – Comparison of Social Security Participation by Age					
	SIPP Estimate	SIPP 90% Confidence Interval	Social Security	Difference	Ratio
Less Than 62	8,076,607	(7,797,583, 8,355,631)	10,599,647	2,523,040*	76%
62+	37,657,018	(37,085,941, 38,228,095)	40,248,639	2,591,621*	94%
Total	45,733,625	(45,114,067, 46,353,183)	50,848,286[1]	5,114,661*	90%

* indicates difference is statistically significant at the 10% significance level.
[1] The total for Social Security is from December 2008.
http://www.ssa.gov/policy/docs/statcomps/supplement/2009/5a.html#table5 (Tables 5.A1.1 – 5.A1.8).
In table 5.A1.4, children from all types of participants are separated into age categories, the category of 60-64 with 49,958 children could not be included in the total for Table 2.

The comparisons of SSI for three separate age groups are shown in Table 3. For SSI, SIPP is doing a better job of estimating participation for those less than 64, where the differences between SIPP and SSI totals are not significantly different. However, for those 65 and older SIPP is underestimating SSI participation, only accounting for 71% of the SSI total. This could be the result of respondents being confused between SSI and Social Security. For individuals 65 and older, they could be eligible for SSI if they have a low-income. Low-income is their total income including Social Security benefits that places them below some threshold value.

Table 3 – Comparisons of Supplemental Security Income Participation by Age					
	SIPP Estimate	SIPP 90% Confidence Interval	SSI	Difference	Ratio
Less Than 18	1,073,299	(970,368, 1,176,230)	1,136,978	63,679	84%
18-64	4,300,593	(4,095,671, 4,505,515)	4,302,730	2,137	100%
65+	1,447,451	(1,327,993, 1,566,909)	2,028,993	581,542*	71%
Total	6,821,343	(6,564,365, 7,078,321)	7,468,701	647,358*	91%

* indicates difference is statistically significant at the 10% significance level.

Table 4 shows the 31 states where the difference between SIPP and SNAP totals was statistically significant, there were no significant differences in the remaining nineteen states and Washington DC. Even though the overall estimate for SNAP was within 16% of the program total, individual states varied widely. In two states, Alaska and Idaho, SIPP overestimated the SNAP participation, with SIPP estimates accounting for 170% of participation totals in Alaska and 142% in Idaho. In all other states, SIPP underestimated total participation. In Vermont, the SIPP estimate was only 29% that of the SNAP benchmark. All remaining states accounted for at least 60% of the SNAP total.

Table 5 summarizes the results of the analysis of response rates across different subgroups. While most of the subgroups had some variation in response rates, only three subgroups had a significantly lower response rate than the total. CBSA type had the largest variation of response rates among the subgroups, with those located in a MSA and principal city having a response rate of 77.9% while those not in a principal city or MSA had a rate of 86.8%. High variation in the response rates could indicate certain subgroups are being over- or underestimated in the final

sample, which could lead to nonresponse bias. Those living in the Northeast had the lowest response rate out of all regions, as well as, Black householders compared to Nonblack householders each having a response rate of 77%.

Table 6 summarizes the results of comparing the estimates of the frame variables for the full sample and for respondents only. Two estimates are given for the respondent, one weighted by the baseweight and the other weighted by the nonresponse-adjusted weight. The relative difference is calculated by dividing the percentage of respondents by the percentage of all sampled cases then subtracting one and multiplying by 100. A positive relative difference indicates the group is being overrepresented in the final sample, while a negative difference indicates the group is being underrepresented. Differences between the relative differences calculated using the base weight and nonresponse adjusted weight told us whether the adjustment helped reduce the nonresponse bias. Using the base weight, we see people in rural areas are overestimated by 5% and those not living in an MSA area or in a principal city were overestimated by 8%, while blacks and those in the Northeast were underestimated by 4%. Examining the relative differences after the nonresponse adjustment, we see that the differences for Census Region almost disappear and differences for urban status, CBSA type, and race of householder are all reduced. It is interesting to note that relative differences for the number of household members and age of householder actually increased, but only marginally. For those variables included in the nonresponse adjustment, like region, there was a reduction in nonresponse bias and reductions also in correlated variables like urban/rural status. Our key variables of interest are not used in the nonresponse adjustment, but can benefit from reductions in bias through the correlated frame variables.

Table 7 shows the odds ratios obtained from the logistic regression analysis with the dependent variable indicating interview/noninterview status. Each of the independent variables was treated as categorical with the first level used as the reference group. For understanding odds ratios, a value greater than 1.0 has a positive effect and a value of less than 1.0 has a negative effect. A positive effect implies that the group is more likely to be interviewed compared to the reference group, whereas, a negative effect implies they are less likely to be interviewed compared to the reference group. The Northeast had the lowest odds of responding with the Midwest being 63% more likely, the West 31% more likely, and the South being 17% more likely of being interviewed. Rural areas had greater odds of being interviewed by 37% compared to urban areas. Households with five or more members and householders in the older age categories had greater odds of being interviewed then those with fewer people and younger age groups. Tenure was the only variable tested that did not significantly affect the likelihood of being interviewed.

Table 7 – Odds Ratios for Logistic Regression of Response		
Parameter	**Estimate**	**90% Confidence Interval**
Region (ref = Northeast)		
Midwest	1.625*	(1.495, 1.766)
South	1.166*	(1.094, 1.243)
West	1.312*	(1.218, 1.414)
Tenure (ref = Owned Housing Unit)		
Rented for Cash	0.965	(0.916, 1.015)
Occupied w/o Payment of Rent	1.106	(0.923, 1.324)
Urban/Rural (ref = Urban)		
Rural	1.371*	(1.262, 1.490)
Number of Persons in a HU (ref = 1)		
2	1.100*	(1.033, 1.171)
3-4	1.149*	(1.078, 1.225)
5+	1.245*	(1.130, 1.372)
Age (ref = < 25)		
25-34	0.999	(0.904, 1.104)
35-44	0.958	(0.869, 1.056)
45-54	1.048	(0.948, 1.159)
55-64	1.144*	(1.038, 1.260)
65+	1.280*	(1.154, 1.419)

* indicates difference is statistically significant at the 10% significance level.

4 Discussion and Limitations

From the benchmark study, we can conclude that SIPP is underestimating participation in government programs like Social Security, SSI, SNAP, and Medicare. However, compared to earlier studies of income from most of these sources, the amount of underestimation is similar in magnitude to what was seen in previous panels. Those programs where SIPP estimated income well in 1990, like Social Security and SSI, now have participation rates within 10% of the program totals. It is harder to make comparisons for the other programs included in our analysis. SNAP has taken the place of the food stamp program, which in the 1990 analysis was included in estimates for AFDC. SIPP estimates for SNAP participation are within 16% of the program total, while estimates for AFDC income were less than 25% of the program totals in 1990 [9, pg 132]. Coverage rates for Medicare and Medicaid show significant underestimation of more than 25%, but no previous studies of these programs were completed. It is hard to do a one-to-one comparison across panels being as we did not consider the same key estimates, but it still provides some insight into magnitude of previous bias. Additional key estimates will be considered in future analyses to make more use of the former studies.

In the comparison of response rates, the subgroups with the greatest variation included region, urban/rural status, CBSA type, and race. This indicates there is potential bias due to nonresponse for statistics associated with these variables. However, the total variation was less than 10%, seeming to indicate that if there is similar bias for the key statistics that it would be small.

Studies of the another Census Bureau survey, the National Survey of College Graduates, did a similar study to compare response rates and found variation of less than 15% among the groups [14]. The analysis of frame characteristics also indicated potential bias associated with region, urbran/rural status, CBSA type, and race. Although after applying the nonresponse adjustment, reductions of bias were seen for each of these groups. Even though small biases remained, all subgroups had relative differences less than 5%. This magnitude was also comparable to an analysis done for the NSCG, where only one variable had groups with relative differences greater than 5% [14]. For the number of household members and age of the householder, the relative differences increased for certain subgroups, which is interesting since a similar variable is used in the nonresponse adjustment. This may be a result from using the nine year old frame data, as compared to a more recent guess made by the field representatives.

The logistic regression pointed to similar areas of potential bias, like region and urban/rural, due to certain subgroups' likelihood of responding. This analysis is also a topic for future examination. This model can be used to examine groups of response propensities and help to obtain an overall indicator of how representative our sample is of the entire population. The latter is an idea developed recently at Statistics Netherlands.

Our analysis is limited mainly by the availability of data for both respondents and nonrespodents. For the analyses using frame variables, only approximately 80% of the total sample could be used. Those households that did not have data from the 2000 Decennial Census file were not included, which includes households in very rural areas, as well as, new construction. These cases, may in fact, be different from our subsample and could add or reduce bias for certain statistics. We were also limited by what frame variables were available and their correlation with the variables important to the survey. Unfortunately, our frame variables were only marginally correlated to our key estimates, therefore the analyses we conduct using our frame variables is likely telling us very little about the nonresponse bias that is associated with our key estimates. The benchmark analysis does allow us an estimate of the bias for our key variables, but this is subject to other errors, as well.

5 Conclusion

There seems to be evidence of potential bias due to nonresponse for some statistics in the SIPP based on the analyses we conducted. Underrepresented groups in previous panels like race and metropolitan residents or underestimation of transfer payment programs, may still remain in the current panels, even with the nonresponse adjustment. However, the magnitude of most of the biases found for the frame variables were small. The differences seen in the benchmark study could be due to response or measurement error coming from various aspects of the interview, affecting the respondent's ability to respond accurately.

Future analyses that take into account the longitudinal aspect of the survey and take advantage of other variables known for all sample cases may help to get a better picture of the overall bias associated with nonresponse. Data on all key statistics are available for those that drop out after Wave 1, comparing these nonrespondents to those that respond in future waves will be our next avenue to pursue. Several studies of previous panels have focused on this and could be used as a comparison. As for the bias associated with Wave 1 nonresponse, it seems that only matching to

administrative records or doing a nonresponse follow-up will allow us to truly quantify the nonresponse bias for the key SIPP statistics.

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Table 4 – Supplemental Nutrition Assistance Program Comparisons by State					
State	SIPP Estimate	SIPP 90% Confidence Interval	SNAP	Difference	Ratio
Alabama	404,069	(340,842, 467,296)	593,827	189,758*	68%
Alaska	101,478	(69,777, 133,179)	59,669	-41,809*	170%
Arkansas	271,146	(219,341, 322,951)	381,255	110,109*	71%
Colorado	191,762	(148,190, 235,334)	259,006	67,244*	74%
Florida	1,248,309	(1,137,336, 1,359,283)	1,576,981	328,672*	79%
Georgia	829,173	(738,665, 919,681)	1,086,410	257,237*	76%
Hawaii	70,818	(44,334, 97,302)	101,656	30,838*	70%
Idaho	150,521	(111,915, 189,127)	105,822	-44,699*	142%
Illinois	961,236	(863,808, 1,058,664)	1,335,447	374,211*	72%
Indiana	498,855	(428,614, 569,096)	652,769	153,914*	76%
Iowa	171,919	(130,662, 213,177)	270,829	98,910*	63%
Kansas	138,314	(101,306, 175,322)	191,580	53,266*	72%
Kentucky	452,529	(385,624, 519,434)	648,602	196,073*	70%
Louisiana	483,877	(414,697, 553,057)	668,572	184,695*	72%
Maine	121,986	(87,230, 156,742)	177,638	55,652*	69%
Maryland	298,877	(244,490, 353,264)	382,063	83,186*	78%
Michigan	996,227	(897,048, 1,095,406)	1,278,720	282,493*	78%
Minnesota	225,382	(178,147, 272,617)	301,389	76,007*	75%
Missouri	439,776	(373,819, 505,733)	724,438	284,662*	61%
New Jersey	371,806	(311,153, 432,459)	455,068	83,262*	82%
North Carolina	706,632	(623,062, 790,202)	993,081	286,449*	71%
Ohio	1,047,219	(945,542, 1,148,896)	1,178,935	131,716*	89%
Oklahoma	358,106	(298,579, 417,633)	425,679	67,573*	84%
Oregon	399,287	(336,435, 462,139)	491,022	91,735*	81%
Rhode Island	53,425	(30,422, 76,429)	88,423	34,998*	60%
South Carolina	412,212	(348,352, 476,072)	614,975	202,763*	67%
South Dakota	39,678	(19,853, 59,503)	64,133	24,455*	62%
Tennessee	834,068	(743,294, 924,842)	940,414	106,346*	89%
Vermont	16,465	(3,694, 29,236)	57,672	41,207*	29%
Virginia	347,755	(289,094, 406,416)	562,781	215,026*	62%
Washington	363,752	(303,759, 423,746)	573,891	210,139*	63%

* indicates difference is statistically significant at the 10% significance level.

Table 5 - Response Rates Across Subgroups

Characteristics	Unweighted Frequency	Response Rate (%)	Std Error	90% Confidence Interval		Difference from total
				Lower	Upper	
Total	42,379	80.5	0.25	80.0	80.9	-
Region						
Northeast	9,315	77.0	0.46	76.1	77.8	3.5*
Midwest	9,605	84.5	0.54	83.6	85.4	-4.0*
South	13,719	79.5	0.47	78.8	80.3	1.0*
West	9,740	81.0	0.52	80.2	81.9	-0.5
Urban						
Rural	5,790	84.7	0.62	83.6	85.7	-4.2*
Urban	36,589	79.8	0.25	79.4	80.2	0.7*
Within PSU Strata						
Non Low Income Strata	30,018	80.4	0.26	80.0	80.8	0.1
Low Income Strata	12,361	80.7	0.47	79.9	81.5	-0.2
CBSA type						
Located within MSA in principal city	16,100	77.9	0.37	77.3	78.5	2.6*
Located within MSA not principal city	20,992	80.9	0.33	80.3	81.4	-0.4
Not in MSA or principal city	5,287	86.8	0.59	85.8	87.8	-6.3*
Black Householder						
NonBlack	37,178	80.9	0.25	80.5	81.3	-0.4
Black Householder	5,201	76.8	0.65	75.8	77.9	3.7*
Number of Household Members[1]						
1	10,091	79.1	0.50	78.3	80.0	1.4*
2	19,792	80.9	0.30	80.4	81.4	-0.4
3-4	9,707	80.9	0.44	80.2	81.6	-0.4
5+	793	80.6	1.31	78.4	82.8	-0.1
Age of Householder						
Less than 25	3,962	79.7	0.71	78.5	80.9	0.8
25-35	6,873	79.4	0.54	78.5	80.3	1.1
35-55	17,867	79.7	0.30	79.2	80.2	0.8*
Over 55	13,677	82.1	0.40	81.5	82.8	-1.6*
Gender						
Male Householder	27,041	80.8	0.29	80.3	81.2	-0.3
Female Householder	15,338	79.9	0.40	79.2	80.6	0.6
Tenure						
Owner	28,505	81.1	0.29	80.6	81.6	-0.6
Renter	13,874	79.0	0.38	78.3	79.6	1.5*

* indicates difference is statistically significant at the 10% significance level.

[1] The category "Number of Household Members" does not include 1,996 respondents that indicated 0 household members.

Table 6 - Comparison of Estimates for Frame Variables

	All Sample Cases		Respondents					
			Base Weight			Nonresponse Adjusted Weight		
	Percent	Std Error	Percent	Std Error	Relative Difference (%)	Percent	Std Error	Relative Difference (%)
Region								
Northeast	21.5	0.29	20.6	0.31	-4.37	21.5	0.33	0.05
Midwest	22.7	0.36	23.8	0.39	5.03	22.6	0.38	0.18
South	32.2	0.42	31.8	0.45	-1.15	32.2	0.46	-0.12
West	23.7	0.25	23.8	0.27	0.68	23.7	0.28	-0.04
Urban								
Rural	13.8	0.39	14.5	0.43	5.29	14.2	0.41	-2.68
Urban	86.2	0.39	85.5	0.43	-0.85	85.8	0.41	0.43
Within PSU Strata								
Non low Income Strata	78.6	0.26	78.5	0.27	-0.10	78.8	0.27	-0.23
Low Income Strata	21.4	0.26	21.5	0.27	0.37	21.3	0.27	0.84
CBSA type								
Located within MSA in principal city	37.4	0.37	36.2	0.72	-3.16	37.2	0.71	0.59
Located within MSA not principal city	50.9	0.78	51.1	0.83	0.51	50.9	0.80	-0.14
Not in MSA or principal city	11.7	1.06	12.7	1.14	7.84	11.9	1.09	-1.36
Race of Householder								
NonBlack	89.3	0.18	89.8	0.20	0.54	89.5	0.21	-0.24
Black Householder	10.7	0.18	10.2	0.20	-4.48	10.5	0.21	1.96
Number of Household Members								
1	24.8	0.21	24.4	0.25	-1.61	25.1	0.26	-1.13
2	49.4	0.29	49.7	0.34	0.55	49.9	0.34	-1.03
3-4	24.0	0.25	24.1	0.28	0.54	23.3	0.27	2.92
5+	1.9	0.07	1.9	0.07	0.00	1.8	0.07	4.86
Age of Householder								
Less than 25	8.8	0.14	8.7	0.15	-0.91	8.8	0.15	0.57
25-35	16.0	0.21	15.7	0.24	-1.32	15.6	0.24	2.32
35-55	42.6	0.29	42.2	0.31	-0.92	41.8	0.32	1.83
Over 55	32.7	0.28	33.3	0.32	2.08	33.9	0.32	-3.70
Gender of Householder								
Male	65.6	0.22	65.8	0.25	0.38	65.4	0.25	0.21
Female	34.5	0.22	34.2	0.25	-0.73	34.6	0.25	-0.41
Tenure								
Owner	69.4	0.21	70.0	0.26	0.84	69.6	0.26	0.24
Renter	30.6	0.21	30.0	0.26	-1.90	30.4	0.26	-0.56