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## Is the Consumer Expenditure Survey Representative by Income?

John Sabelhaus, David Johnson, Stephen Ash, David Swanson, Thesia I. Garner, John Greenlees, and Steve Henderson

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### 8.1 Introduction

Aggregate spending in the Consumer Expenditure Survey (CE) is well below comparable personal consumption expenditures (PCE) in the National Income and Product Accounts (NIPA), and the ratio of spending in the CE to spending in the NIPA has fallen from where it was two decades ago.<sup>1</sup> Assuming NIPA values are a good benchmark, two potential reasons for the aggregate spending difference are that higher-income families (who presumably spend more than average) are underrepresented in the CE estimation sample, or there is systematic underreporting of spending by at least some CE survey respondents.<sup>2</sup> Resolving why the aggregate shortfall

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1. Crossley (2009) shows that the same basic conclusion holds for the British equivalent of the CE survey.

2. As discussed in Garner et al. (2006), there are possible components for which PCE may be overstated.

**Table 8.1** Ratio of Consumer Expenditure survey aggregates to comparable NIPA personal consumption expenditure measures

Year	Ratio of CE to PCE for comparable categories				
	All goods and services	Durable goods	Nondurable goods	Owned housing	Other services
<i>Garner, McClelland, and Passero (2009)</i>					
1992	0.88	0.88	0.69	1.23	0.90
1997	0.88	0.80	0.67	1.26	0.86
2002	0.84	0.75	0.63	1.25	0.82
2003	0.82	0.79	0.61	1.26	0.80
2005	0.83	0.75	0.63	1.26	0.81
2007	0.81	0.69	0.61	1.30	0.81
<i>BLS published estimates based on latest NIPA crosswalk</i>					
2005	0.80	0.69	0.67	1.16	0.75
2006	0.80	0.67	0.67	1.17	0.75
2007	0.79	0.65	0.65	1.22	0.73
2008	0.78	0.64	0.67	1.15	0.73
2009	0.78	0.66	0.66	1.10	0.73
2010	0.75	0.62	0.63	1.09	0.71

occurs is important for weighting the Consumer Price Index (CPI) and for various research questions that involve the joint distribution of spending and income, including measuring inequality, studying savings behavior, and evaluating the distributional burden of consumption taxes.

Establishing the basic facts about the accuracy of aggregate CE spending is straightforward in principle, but complicated in practice because the CE and PCE differ in terms of both spending concepts and population coverage.<sup>3</sup> However, piecing together the latest Bureau of Labor Statistics (BLS) estimates with the results of a study by Garner, McClelland, and Passero (2009) provides a compelling story (table 8.1). There are systematic differences across types of spending at any point in time, and there is also a general decline in the ratio of CE to PCE by about 10 percentage points between 1992 and early in the first decade of the twenty-first century. However, since 2003, the CE-to-PCE ratio has been relatively stable, both overall and within broad categories of spending.

On net, in 2010 the CE appears to be capturing 75 percent of comparable PCE. The CE is lower in most categories, but rental equivalence of owned housing is a rare exception where the CE is higher than the PCE.<sup>4</sup> If it is omitted, the CE's estimates of comparable spending are generally about one-third lower than the PCE. In particular, the ratios for

3. For example, PCE includes consumption spending by nonprofit institutions.

4. For a discussion of how owned-housing services are estimated in the CE, see Garner and Short (2009).

durables, nondurables, and nonhousing services are 62, 63, and 71 percent respectively.<sup>5</sup>

Although CE is fundamentally designed to collect expenditure data, not income data, a failure to reflect the income distribution accurately could suggest that inaccuracies occur in the spending distribution as well. There is evidence that the CE does not capture as much income as in other surveys, and the missing income seems to be at the top of the income distribution. Passero (2009) shows that the CE aggregate income is only 94 percent of Current Population Survey (CPS) aggregate income.<sup>6</sup> Evidence that the missing CE income occurs at the very highest income levels comes from comparing CE against other data sets. A comparison of the CE income distribution to the CPS, Survey of Consumer Finances (SCF), and tax return-based Statistics of Income (SOI) data sets suggests significant underrepresentation of the \$100,000 or more income group in the CE. The CE finds fewer households in that income range, and average incomes for households that are above \$100,000 are below the averages in the other data sets.

It may be that higher-income CE households are simply less likely to accurately report their incomes, but there are also good reasons to suspect that the households at the very top of the income distribution are underrepresented in the CE. The first type of evidence comes from a new approach to this question developed for this chapter. The approach involves linking all CE-sampled households (both respondents and nonrespondents) to the average adjusted gross income (AGI) in their five-digit zip code area.<sup>7</sup> For most of the AGI distribution there is little or no association between unit nonresponse and zip code-level AGI, but at the very top of the income distribution the unit response rate and the ratio of average CE income to mean zipcode-level AGI are both lower. That is, in the top few percentiles of households sorted by zip code-level AGI, households are less likely to participate in the CE, and those households that do participate are more likely to have incomes below the average in their zip code.

This difference in participation suggests that high-income households are underrepresented in the CE; however, underreporting of spending for at least some respondents is also quite likely. The CE tabulations (reproduced in this chapter) show that CE expenditures are lower than income, which suggests unusually high savings rates (even after accounting for measurement differences in income and spending). In addition, CE data show that the ratio of spending to after-tax income falls with income, suggesting very high savings rates at the top of the income distribution. Comparison of CE incomes to

5. Other chapters in this volume consider how more detailed categories of spending in the CE compare with external benchmarks. See Bee, Meyer, and Sullivan (chapter 7) and Passero, Garner, and McCully (chapter 6).

6. See also Meyer, Mok, and Sullivan (2009).

7. The analysis here is based on the Consumer Expenditure Quarterly interview survey (CEQ). In principle, the same exercise could be done with the Consumer Expenditure diary survey (CED).

other data sources suggests that as much as 25 or even 50 percent of income is missing in the \$100,000 or more income group. As a result, if this income underreporting is simply due to underreporting for high-income households, this would imply even larger discrepancies in average savings rates between those implied in the CE data and other data sources (e.g., SCF).

Why is it important to distinguish between the possible explanations for underreporting of aggregate CE spending? The difference in CE to PCE aggregates across the broad categories in table 8.1 highlights one key reason—weighting the CPI. If there are systematic differences in how well the CE survey captures aggregate expenditures across categories, the CPI weights will be biased, and the overall index will be inappropriately affected by changes in the prices of over- or underrepresented categories.<sup>8</sup> Given the plutocratic nature of the CPI, the relationship of income and spending on different types of categories suggests that underrepresentation of high-income families in the CE could be biasing the CPI.

In addition to weighting the CPI, however, there are also several research areas where the ratio of expenditures to income across income groups is the crucial input, and thus distinguishing between underrepresentation of high-income families versus underreported expenditures for at least some respondents is crucial. The CE data have been used in several studies to measure differences between consumption expenditure and income inequality, with consumption-expenditure inequality shown to be consistently and dramatically lower.<sup>9</sup> Bosworth, Burtless, and Sabelhaus (1991) used CE data to track changes in household saving across groups and time, and the estimated patterns of low-income dissaving and high-income saving are dramatic in every period. Finally, CE data are regularly used by government agencies and other groups to measure the distributional burden of consumption taxes. Consumption taxes appear very regressive, because the ratio of spending to income falls dramatically with income.

If the source of the aggregate CE shortfall is simply underrepresentation of the highest-income households, then the inequality, saving, and tax distribution studies described above may be incomplete, but they are not necessarily biased for the range of the income distribution they represent. Even though the very highest-income households are underrepresented in the CE, Sabelhaus and Groen (2000) demonstrate that the overall underreporting of spending is partially attributable to underreporting of expenditures by at least some CE respondents.<sup>10</sup> If expenditure underreporting is indeed worse

8. See McCully, Moyer, and Stewart (2007). See also Blair (chapter 2, this volume), prepared for this conference.

9. See, for example, Johnson and Shipp (1997), Short et al. (1998), Attanasio et al. (2002), Krueger and Perri (2006), Krueger et al. (2010), and Heathcote, Perri, and Violante (2010).

10. Sabelhaus and Groen (2000) use a variety of techniques, including appealing to consumption-smoothing theory, to argue that the ratio of consumption to income for high-income families is biased down.

for higher-income households, then the results of the CE-based inequality, saving, and tax-distribution research should be revisited.

## **8.2 How Does the CE Income Distribution Compare to Other Data Sources?**

Although the CE estimation sample reflects the actual distribution of households by income over most ranges, comparisons between the CE and other household surveys suggest that the very highest-income families are underrepresented. In this section, weighted counts of CE units and average incomes are compared against three other data sources—the Current Population Survey (CPS), the Survey of Consumer Finances (SCF), and the IRS tax-return-based Statistics of Income (SOI). The comparisons include one data set (CPS) that is similar to the CE in sampling strategy but more focused on income, one that is purely administrative (SOI), and one that employs differential sampling for high-wealth households in order to capture the top of the wealth distribution (SCF). To enhance comparability for this study, CPS and SOI incomes do not include the value of capital gains since the CE income does not include gains in income.

The overall count of sampled units in the CE, CPS, and SCF are similar. Although the CE samples “consumer units,” the CPS samples “households,” and the SCF samples “primary economic units,” the overall counts for any given year are within 2 or 3 percent (table 8.2, last column). The count of units for the SOI is very different from the other surveys because dependent filers—usually children living in their parents’ home—may have to file their own tax returns. There are also differences in the income concept in the SOI because nontaxable forms of income (mostly transfers) are not included in adjusted gross income (AGI). After adjusting for those differences, though, the four data sets are broadly consistent across the income categories.

The well-known skewness of the US income distribution shows up clearly in the CE as one moves from less than \$50,000 of income (65.1 million consumer units), to between \$50,000 and \$100,000 (34.9 million), to \$100,000 or more (18.9 million). The counts of units for the CPS, SCF, and SOI are shown as differences from the CE values, and the general impression one gets is that the differences are second order. All three data sets show the same basic shape. The SOI, as expected, finds many more units in the less than \$50,000 group because of dependent filers and the fact that nontaxable transfers are not being included.

The focus of the analysis here, however, is the top of the income distribution, and although the counts of units are broadly similar in the \$100,000 or more income category, the total income received by that group is much lower in the CE than in the other three data sets. For example, the CPS finds 22.1 percent more income for those households. Although much of that is because the CPS finds more households above the \$100,000 line, there is no

**Table 8.2**      **Income distribution in the Consumer Expenditure survey and three other data sets, 2006**

	Income category			
	Less than \$50,000	\$50,000 to \$99,999	\$100,000 or more	All incomes
<i>Consumer Expenditure survey</i>				
Number of units (millions)	65.1	34.9	18.9	118.8
Total income (billions \$)	1,589	2,472	3,111	7,172
<i>Differences from Consumer Expenditure survey</i>				
<i>Current Population Survey</i>				
Number of units (millions)	-5.5	-0.6	3.2	-2.8
Total income (billions \$)	-85	-51	688	551
Total income (percent)	-5.3	-2.1	22.1	7.7
<i>Survey of Consumer Finances</i>				
Number of units (millions)	-1.6	-2.7	1.5	-2.7
Total income (billions \$)	11	-166	1,832	1,677
Total Income (percent)	0.7	-6.7	58.9	23.4
<i>Statistics of Income</i>				
Number of units (millions)	27.2	-4.9	-2.8	19.6
Total income (billions \$)	210	-353	1,002	859
Total income (percent)	13.2	-14.3	32.2	12.0

*Notes:* The SCF and SOI income exclude capital gains.

reason to expect any divergence at all between the CE and CPS because the sampling approach and income concepts are similar.<sup>11</sup>

The more noticeable differences in top incomes occur when one compares CE (and CPS) to the SCF and the SOI. The SCF uses an income concept that generally matches the CE, but employs a different sampling strategy in order to capture the top of the wealth distribution.<sup>12</sup> The SCF finds nearly 60 percent more income in the \$100,000 or more income range. To put those numbers in perspective, the nearly \$2 trillion of additional income that the SCF finds at the very top is similar in magnitude to the aggregate spending mismatch that motivates this study.

11. A major difference between the CPS and CE surveys is that the CPS is focused on collecting income, while the CE is focused on spending, which could account for some of the difference in the quality of income reporting. Another difference is that CE income data are only collected in the second and fifth interviews, with the second interview values carried over to the third and fourth interviews. There are also differences between the CPS and CE in terms of imputation and top-coding procedures. See Passero (2009) and Paulin and Ferraro (1996) for a discussion of income imputation in the CE, and Burkhauser et al. (2009) for a discussion about how using the CPS without top codes affects estimates of the incomes at the very top of the income distribution.

12. For a general discussion of the SCF see Bucks et al. (2009), and for a general discussion of SCF design and implementation, see Kennickell and Woodburn (1999). The SCF sampling strategy is focused on wealth measurement, but Kennickell (2009) describes how wealth and income are related.

The conceptual differences between CE and the SOI make direct comparisons more problematic. Using an AGI income concept with the CE data will yield an even lower estimate of income. However, the SOI still finds over 30 percent more income in the \$100,000 or more range even though there are fewer tax filers in that AGI range because of the differences between AGI and the more generalized income concept used in the other surveys. Thus, on net, comparing the CE to both the SOI and SCF data suggests that the very highest income households are underrepresented in the CE (and in the CPS, though to a lesser extent).

### **8.3 Why Does the CE Underrepresent the Very Highest Income Households?**

The CE is designed to collect expenditure data and related demographic characteristics from a sample that is representative of the US civilian non-institutional population; the weighting procedures to ensure this representativeness do not account for income. However, if the variables used to produce representative expenditure estimates are highly correlated with income, then the CE random-sampling approach should still generate an unbiased representation of the true population income distribution. However, two problems associated with sampling could lead to the underrepresentation of very high income households.

The first potential problem is sampling variability because income is highly concentrated at (and even within) the top percentiles, as indicated in both tax data and targeted surveys like the SCF. Sampling variability implies that the estimated aggregates will be very dependent on whether those probabilistically rare households are chosen to participate in the survey. The fact that CE incomes are systematically lower at the top end—and not just extremely volatile at the top end—implies that sampling variability is not the problem.

The second possible problem is differential unit nonresponse.<sup>13</sup> The concern here is that the highest-income households are less likely to participate in the survey when they are selected. The fact that incomes are systematically lower at the top end of the income distribution in the CE suggests that differential unit nonresponse among very high income households is an explanation worth exploring, and that is the focus of this section.

There is no direct way to assess whether or not the very highest income families are less likely to participate in the CE when they are chosen because we do not observe the actual incomes of nonparticipants. However, it is possible to make indirect inferences about survey participation using a new data set that links sampled CE units to the average adjusted gross income (AGI)

13. The discussion here follows a long literature on unit nonresponse. See, for example, Groves (2006) and King et al. (2009) for useful introductions to that literature.



in their five-digit zip code area. The average AGI values linked to sampled CE units are produced by the IRS Statistics of Income Division, and are available for public use.<sup>14</sup>

The data set built for this analysis starts with all consumer units selected for the CE for calendar years 2007 and 2008.<sup>15</sup> There are 104,830 units selected for participation, and 74 percent of those participated in the survey. However, the BLS excludes the first (or “bounding”) interview when publishing expenditure estimates for publication, and that approach is followed here. Thus, the final data set includes 61,546 interviewed respondents out of 83,366 in-scope sampled units, which is an overall response rate of 74 percent.

The analysis here is based on sorting the sampled CE households into income groups using the average AGI for their zip code. This makes it possible to sort both respondents and nonrespondents using the same income measure, and to test for differences in response rates across AGI percentiles. Basically, the first step uses the average response rates for the CE sample in each of the 100 AGI percentile-income groups. The second step is to compare the average incomes of respondents to the average AGI for their zip code, again, by AGI percentile. Note that in both steps the percentile-cell calculations all involve several hundred observations being averaged to create the estimated response rates or the ratio of average CE income to average AGI.

### 8.3.1 Using Zip Code-Level AGI to Sort Households

Using zip code-level AGI to proxy “true” income of nonrespondents does raise a few concerns. First, the AGI concept itself is an imperfect measure of income because it excludes nontaxable transfers along with other tax-free income such as municipal bond interest. The idea of nontaxable transfers usually evokes images of food stamps and other income maintenance programs, but it is probably more salient to note that for most Social Security recipients, most or all of their Social Security is excluded from AGI. Thus, a retiree with \$20,000 in taxable pensions and \$20,000 in Social Security will show up with an AGI of \$20,000, even though the CE would identify them as having \$40,000 of income.

The second problem with using zip code-level mean AGI is the presence of dependent filers. As noted in the discussion of table 8.2 in the previous section, the count of SOI “units” is much higher than CE consumer

14. (See <http://www.irs.gov/taxstats/indtaxstats/article/0,,id=96947,00.html>.) To protect confidentiality, the analysis here was conducted by the authors at the Census Bureau and the Bureau of Labor Statistics using internal data with only zip code information.

15. The data set covers all units who were interviewed in the CE from the first quarter of 2007 through the first quarter of 2009, and thus will include expenditures that occurred early in 2009 or late in 2006. All income and expenditure values (including zip code-level AGI) are inflated to 2008 dollars from their reference periods using the CPI-U.

units or CPS households, because dependent children with income may file separate returns. Although the CE income calculations have been adjusted to more closely resemble the AGI income,<sup>16</sup> both of these problems with using AGI—that AGI excludes nontaxable income and the averages include dependent filers—imply that average AGI for the zip code is a downward biased estimate of average household income. In the first case AGI income may exclude some income components, and in the second we are splitting the household-level income across too many units. As figure 8.2 illustrates, the overall mean of CE income is about 14 percent higher than the mean of zip code-level AGI for the same zip code areas.

The third problem with using zip code-level AGI is that it excludes nonfilers, but in this case there is no obvious bias in average AGI. Households who receive only nontaxable transfers will not even show up in the SOI zip code-level data file, because they are not required to file tax returns. Their exclusion from the zip code file would reduce the total number of units, but would likely not change the income ranking of the zip codes. That is, if a \$20,000 per year Social Security recipient lives in the same zip code as a \$20,000 per year wage earner, we would only observe the wage earner in the zip code AGI file, but the \$20,000 AGI would still be a good estimate of income for both households in the zip code. Even if this is not an accurate assumption (see the next paragraph), the exclusion of nonfilers is unlikely to affect the highest income zip code areas, which are of most interest here.

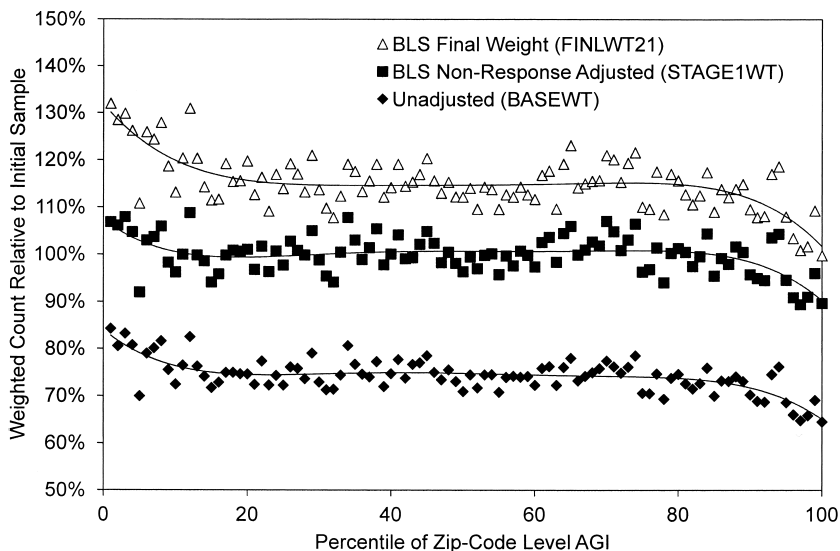
The final problem with using zip code-level AGI is that zip code may not be a narrow enough geographic classifier from a socioeconomic perspective, meaning there is significant income variation within zip codes. This potential problem motivates the second step of the approach implemented here, because in addition to looking for differences in response rates by AGI percentile, we also consider the ratio of CE respondent-reported incomes to average AGI. This second step is designed to capture differences in response by income within zip codes and thus control for variations in within zip code incomes, especially at the top of the distribution where our attention is focused.

### 8.3.2 Response Rates by AGI Percentiles

The first question addressed using the new zip code-linked data set is whether the probability of responding to the survey, when sampled, varies systematically with income.<sup>17</sup> All sampled CE units are assigned the average AGI for their zip code, and the entire data set is sorted into one hundred percentile groups (0–1st, 1st–2nd, . . . 99th–100th). Although in principle

16. For the analysis in sections 8.3 and 8.4, the CE and SOI income concepts have been made more comparable (see footnote 20).

17. Note that we are not testing whether or not the probability of being sampled varies with zip code-level income, though in principle that could be accomplished by comparing the sampled CE population against the entire SOI zip code data set.



**Fig. 8.1** Consumer Expenditure survey (CE) response rates by zip code-level adjusted gross income (AGI) percentile

*Note:* Fitted curves are fifth-order polynomials.

this is a simple calculation, because response is a binary outcome the analysis is complicated to some extent because it requires acknowledging the potential effects of existing BLS poststratification (weighting) adjustments.

The simplest calculation involves the inverse of the raw sampling probability, which BLS refers to as BASEWT. The values for BASEWT in the CE are typically around 10,000, which means that a consumer unit in the sample represents 10,000 consumer units in the US civilian noninstitutional population—itsself plus 9,999 other consumer units that were not selected for the sample.<sup>18</sup> Using BASEWT, the simplest calculation of response by AGI involves taking the ratio of respondents (weighted by BASEWT) to sampled units (also weighted by BASEWT) within each AGI percentile (figure 8.1, lowest set of markers).

The overall response rate across AGI percentiles is 74 percent for 2007 and 2008.<sup>19</sup> Figure 8.1 shows that the response rate for most AGI deciles

18. There are some relatively minor adjustments to BASEWT that adjust for several types of operational and field subsampling. Examples of when subsampling is used include when a data collector visits a particular address and discovers multiple housing units where only one housing unit was expected or when more units are found in the listing than expected in rural areas that use an area frame.

19. The fact that the BASEWT response rate of 74 percent exactly matches the response rates based on simple sample counts, as noted earlier, underscores the fact that the adjustments to BASEWT are empirically very small.

is between 70 and 80 percent for most of the AGI distribution. Although the numbers exhibit a fair amount of variability, there is no clear pattern between (roughly) the 10th and 90th percentiles. The data do show lower response for the highest AGI percentiles, which confirms the hypothesized higher unit nonresponse for very high income families. Overall, the response rate for the top 5 percentiles is 66 percent, and the top 1 percent by AGI has a response rate of 65 percent.

Interestingly, the response rates by AGI are higher than average at the bottom of the AGI distribution. The overall response rate based on BASEWT is 80 percent for the bottom 5 percentiles and 84 percent in the 1st percentile. Given the very large sample sizes involved in these calculations—over 800 sampled units in each AGI percentile—these higher response rates for lower-income zip codes are noteworthy. Although we do not pursue an explanation for higher unit nonresponse by lower-income households here, it is certainly an interesting area for further research, and it is worth noting that the sample is certainly not underrepresentative for studying poverty and related topics.<sup>20</sup>

Although the unadjusted response rates (based on BASEWT) suggest that higher-income households are indeed underrepresented in the CE respondent sample, there are two subsequent stages of BLS poststratification that could remedy this underrepresentation.<sup>21</sup> The first step involves the “non-interview” adjustment factor, which involves applying differential adjustments based on estimated nonresponse patterns (this adjustment creates what BLS calls STAGE1WT). Specifically, this factor adjusts for interviews that cannot be conducted in occupied housing units due to a consumer unit’s refusal to participate in the survey or the inability to contact anyone at the sample unit in spite of repeated attempts. This adjustment is performed separately for each month and “rotation group” (interview number) and yields sixty-four cells or factors based on region of the country, household tenure (owner or renter), household size, and race of the reference person.

If income is correlated with these sixty-four factors that affect unit nonresponse, then applying the noninterview adjustment factor could remedy the differential in response rates at very high (and very low) incomes. However, the correlation between zip code-level AGI and the BLS noninterview adjustment factor appears to be weak as shown in figure 8.1 (middle set of markers). The adjustment factor raises response rates nearly uniformly across AGI percentiles. The overall adjustment factors are calibrated such that the adjusted overall response rate is basically 100 percent, meaning the

20. The other key distinction between the top and bottom of the AGI distribution, explored further below, is that the average reported income in the CE at the top is well below the average AGI at the top, suggesting that the families who do participate in the top zip codes have below average income. At the bottom of the AGI distribution, reported incomes match AGI quite well.

21. The discussion of CE weighting here largely follows the Bureau of Labor Statistics, *Handbook of Methods*, available online at [www.bls.gov/opub/hom/](http://www.bls.gov/opub/hom/).

new weights will sum to the count of originally sampled units, but nearly the same curvature in response rates at very high and very low percentiles is observed. Hence, households in the top 5 percentiles are about 10 percent less likely to participate in the survey than households in the middle 90 percentiles, and the difference is the same regardless of whether BASEWT or STAGE1WT is used to weight the data. This suggests that the CE's noninterview adjustment is not accounting for the different response rates observed at different income levels.

Finally, BLS applies a "calibration factor" that adjusts the weights to twenty-four "known" population counts to account for frame undercoverage. These known population counts are for age, race, household tenure (owner or renter), region, and urban or rural. The population counts are updated quarterly. Each consumer unit is given a calibration factor based on which of the twenty-four distinct groups they are in (this last adjustment creates FINLWT21, the weight that CE microdata users are most familiar with).<sup>22</sup> Similar to the above shift shown in figure 8.1 between using BASEWT and STAGE1WT, the calibration-adjusted (using FINLWT21) response rates are shifted up again (figure 8.1, top set of markers). However, there is no qualitative change in the pattern. As with BASEWT and STAGE1WT, households in the top 5 percentiles are about 10 percent less likely to participate in the survey than households in the middle 90 percentiles.

### 8.3.3 Probit Analysis

An alternative approach to exploring the relationship between income and unit nonresponse involves estimating a binomial probit model in which zip code-level AGI is included as a determinant of response status along with the sixty-four-way matrix of stratifying variables used by the BLS in the weighting adjustment for nonresponse that creates STAGE1WT. Specifically, *NR* (in equation [1] below) is a binary variable that is equal to zero for responding CUs and one for those that did not participate in the survey. The regression also includes sixty-three dummy variables corresponding to all but one of the region-family size-race-housing tenure strata used for the nonresponse weighting adjustment in the CE. A fifth-order polynomial function in AGI is included using five variables: AGI,  $AGI^2/1000$ ,  $AGI^3/10^6$ ,  $AGI^4/10^8$ , and  $AGI^5/10^{10}$ .<sup>23</sup> The equation below is estimated using the same

22. Note that there are infinitely many sets of calibration factors that make the weights add up to the twenty-four "known" population counts, and the CE selects the set that minimizes the amount of change made to the "initial weights" (initial weight = (base weight) × (weighting control factor) × (noninterview adjustment factor)).

23. The functional form was chosen to match the fifth-order polynomial curves in figures 8.1 and 8.2. As in the graphical analysis, AGI and CE income data are made more consistent by subtracting capital gains income from the former and several nontaxable items from the latter: food stamp receipts, cash welfare and SSI benefits, child support receipts, and alimony payments. Using information from 2008 SOI tables, we also subtracted estimated untaxed portions of interest receipts, pension benefits, and Social Security and railroad retirement benefits.

sample of 61,546 responding and 21,820 nonresponding CUs described above, and observations are weighted by BASEWT.

Each of the five AGI variables was asymptotically significant at the 0.01 percent significance level, even with all the stratifying variables held constant. A likelihood ratio test of the significance of the five AGI variables yielded a chi-square value of 180 with five degrees of freedom, which easily surpasses any usual significance level. The probit results of interest are:

$$(1) \quad \text{Probit (NR)} = [\text{stratification dummy terms}] + 0.0104 \text{ AGI} \\ - 0.1133 \text{ AGI}^2/1000 + 0.6373 \text{ AGI}^3/10^6 \\ - 0.1605 \text{ AGI}^4/10^8 + 0.0140 \text{ AGI}^5/10^{10}.$$

This equation implies a positive impact of zip code-level AGI on the nonresponse probability, with the second derivative negative, until the highest-observed values of AGI. All five AGI coefficients were significant at the 1 percent level in a two-tailed test.

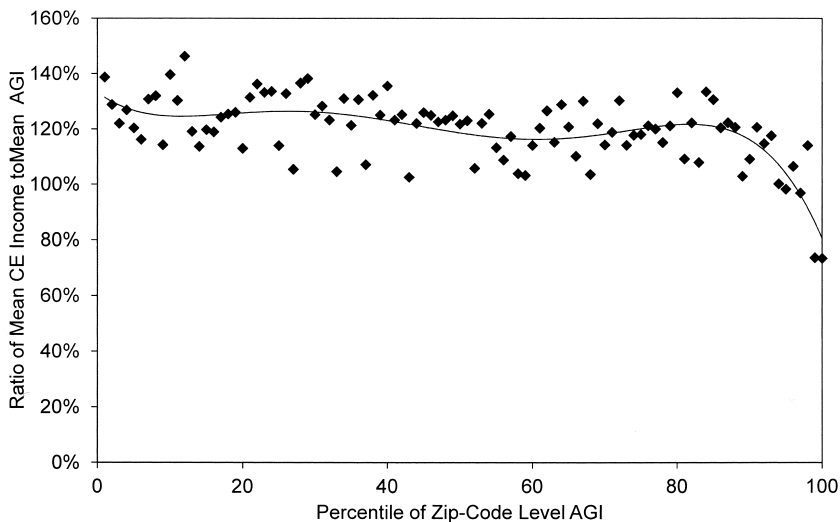
The probit approach is indicative of how one might begin to think about creating an alternative to the BLS stage-one adjustments (STAGE1WT) using AGI along with the existing BLS stratifying variables. With the probit-based noninterview adjustments, the average adjusted response rate in the top 5 AGI percentiles is only about 3 percent below that of the sample as a whole, compared to about 9 percent using the BLS STAGE1WT adjustments and 10 percent using the FINLWT21 adjustments. By giving higher weights to CUs in higher-AGI areas, the probit approach does indeed imply higher aggregate-weighted average CE incomes and expenditures, but the effects are modest.<sup>24</sup>

Using a revised weight based on the probit adjustment using AGI as an explanatory variable yields average income that is only about 0.37 percent higher and average spending that is about 0.19 percent higher than those using the BLS STAGE1WT. Hence, this probit analysis is able to capture the pattern shown in figure 8.1, but adjusting the weights cannot account for all of the income underreporting.

### 8.3.4 CE Incomes Relative to Average AGI

The previous analysis demonstrated that there is a differential nonresponse in the very high income AGI zip code areas. Although the CE income appears to be associated with zip code-level AGI, it is difficult to map these outcomes back to the univariate income distributions shown earlier (table 8.2) because CE households are being sorted by zip code-level AGI, not their

24. It is important to recognize that if the BLS actually used these probit nonresponse adjustments it would necessarily lead to different calibration adjustments. The alternative calibration factors might be expected to reduce the differences between the current and probit-based income and expenditure estimates. Unfortunately, estimating new calibration factors was not feasible for this chapter.



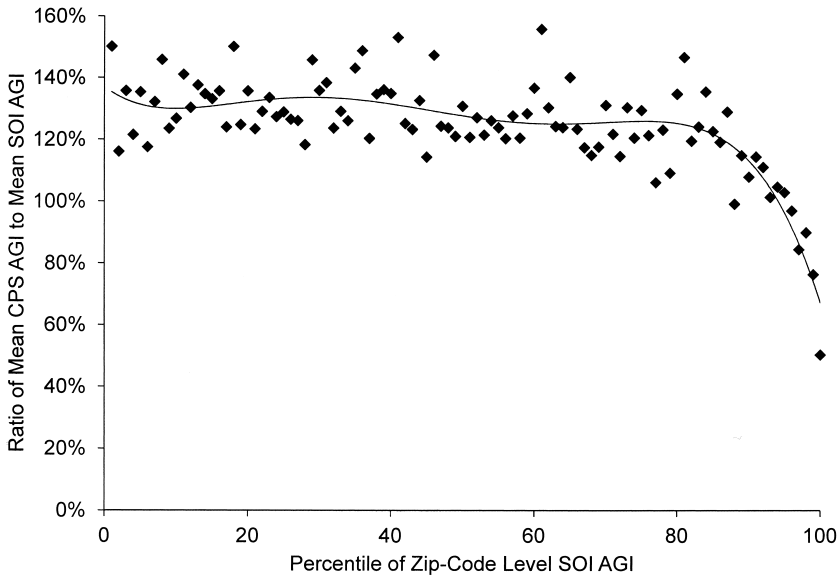
**Fig. 8.2 Ratio of mean Consumer Expenditure survey (CE) income to adjusted gross income (AGI) by zip code-level AGI percentile**

*Note:* Fitted curve is a fifth-order polynomial.

own household income (which we cannot observe for nonrespondents). The next part of the analysis provides more support for the proposition that the very highest income households are underrepresented in the CE.<sup>25</sup> In this second step, we compare average CE income to average AGI within each AGI percentile, and show that the ratio generally falls with income and is dramatically lower at the top of the AGI distribution.

Across all AGI percentiles in the linked data set, mean CE income for respondents (based on FINLWT21) is about 14 percent higher than mean AGI for all sampled units (based on BASEWT, though the exact weight chosen does not affect this answer). However, there is a distinct downward pattern across AGI percentiles (figure 8.2). The ratio of mean CE income to mean AGI is about 140 percent at the bottom of the income distribution, and falls steadily as AGI increases, before plummeting to below 74 percent for the top 2 percentiles of AGI. Thus, figure 8.2 complements figure 8.1 in the following sense. Figure 8.1 shows that households in the top AGI percentile zip codes are 10 percent less likely to participate than the rest of the sample, and figure 8.2 suggests that the households within the top AGI percentiles that do participate are more likely to have lower incomes than the households in that zip code who did not participate. Further, this pattern of

25. In this chapter, we use total CE income, including the incomes imputed by the BLS for consumer units who participate in the survey but who fail to respond to income questions. Imputation would have little effect on the section 8.2 comparisons.



**Fig. 8.3 Ratio of mean CPS adjusted gross income (AGI) to SOI AGI by zip code-level SOI AGI percentile**

*Note:* Fitted curve is a fifth-order polynomial.

high-income areas having lower reported income may be common to many household surveys. Figure 8.3 illustrates a similar pattern using the CPS data and the AGI data by zip code. Similar to figure 8.2, figure 8.3 is based on an analysis using calendar year 2008 CPS income data that are comparable to the AGI income concept and the same SOI file by zip code used in CE analysis. Given these lower survey response rates among very high income households observed in the CE and CPS, it may be that a targeted oversampling strategy such as the one used by the SCF is the only way to get accurate representation at the top of the income distribution.

Although there are conceptual differences between AGI and CE income that make direct inferences difficult, it is worth noting that the combined insights from figure 8.1 and figure 8.2 probably go a long way toward explaining the income distribution differences presented in table 8.2. For example, the CE finds about 7 percent fewer households above \$100,000 than the SCF, which is similar in magnitude to the roughly 10 percent response differentials for the top 5 percentiles shown in figure 8.1. Also, the ratio of average income in the CE to average income in the SCF for households above \$100,000 is 68 percent, which is in the same ballpark as the CE income to AGI ratios at the highest AGI percentiles. Although a direct mapping from the zip code-level AGI percentile analysis to univariate income distributions requires more research, the results here suggest that differential unit nonresponse



probably goes a long way toward explaining the shortfalls. To fully incorporate the effects of differential unit nonresponse into formal poststratification adjustments requires comparable income measures. A more complete analysis involves more fully reconciling the CE income and AGI concepts, which is a topic for future research. See the earlier discussion in the text about why AGI and CE income concepts diverge.

#### **8.4 Why is Aggregate Consumer Expenditure Survey Spending So Low?**

If PCE in the National Income and Product Accounts (NIPA) are viewed as the truth about what consumers actually spend in a given time period, there are two possible high-level explanations for why aggregated spending in the CE is below the corresponding PCE totals. The evidence above provides some support for the first reason, which is that the very highest income households are underrepresented. However, the observed underrepresentation of very high-income households cannot fully explain the aggregate CE spending shortfall. The most extreme estimate of the aggregate CE income shortfall above \$100,000 comes from comparing the CE to the SCF. The SCF finds about \$1.7 trillion more income above \$100,000 than the CE, but if one applies the BLS-reported ratio of expenditures to gross income for that group (61 percent), that implies total spending would rise by 16 percent, which explains perhaps half of the overall shortfall relative to PCE totals (as shown in table 8.1).

Overall, published CE expenditures are lower than published CE after-tax incomes. For example, the ratio of published total expenditures to published after-tax income for CE respondents was 83 percent in 2006.<sup>26</sup> Given the relationship between aggregate spending and disposable income in the NIPA data, that ratio probably should have been much higher.<sup>27</sup> Based on that aggregate perspective and the conclusion that misrepresented high-income households only explains at most half of aggregate underreporting; at least some of the shortfall in aggregate CE spending seems attributable to underreporting of spending (given income) by at least some CE respondents.

26. These calculations are based on published BLS numbers, even though the reported values have both conceptual problems and systematic reporting errors in at least one key variable. Conceptually, for example, BLS counts Social Security taxes and employee contributions to pensions as expenditures, but they do not count mortgage principal repayments as spending. For these and other reasons the concept of after-tax income minus expenditures is not in any sense a pure “saving” estimate, but there are biases in both directions, and fixing those would require unavailable information such as net home equity extraction needed to measure net mortgage principal payments. There are also some measurement biases in the table that BLS is aware of and working on—for example, based on comparison of effective tax rates with other sources, underreporting of income taxes could account for several percentage points of the overall cash-flow discrepancy, and even more for higher-income respondents.

27. See, for example, Bosworth, Burtless, and Sabelhaus (1991) for a discussion of what is involved with reconciling aggregate and household-level saving concepts.

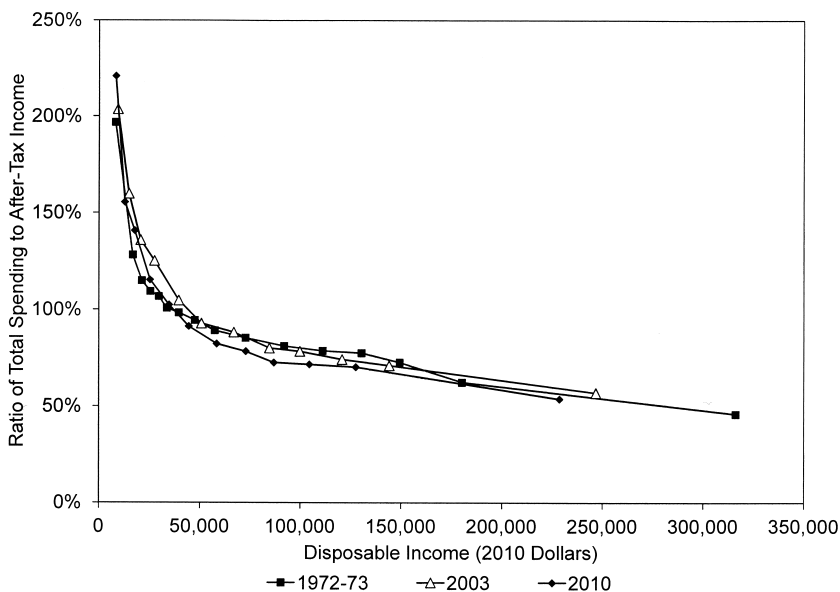
Knowing that the overall spending-to-income ratio seems too low for the CE survey (based on comparisons to PCE) is a starting point, but it does not help with the distributional question of whether the propensity to underreport spending varies with income itself. Researchers interested in using the CE for distributional analysis of questions about topics like consumption-expenditure versus income inequality, saving rates, or the distributional burden of consumption taxes, rely completely on the empirical joint distribution of expenditures and income. If the problem is proportional underreporting of expenditures for all CE respondents, then the simple solution is to scale up spending for all households (perhaps by type of spending) before undertaking any distributional analysis (see Slesnick [2001] and Meyer and Sullivan [2011] for a similar approach). However, if the propensity to underreport rises with spending (and thus with income), then some sort of differential adjustments are warranted.

The estimated pattern of spending-to-income ratios by income in the CE may have flaws, but if it does, those flaws are not a new phenomenon. A comparison of published BLS data for 1972–1973, 2003, and 2010 in figure 8.4 shows that the ratio of spending to unadjusted after-tax income at any given level of income has not changed much in forty years.<sup>28</sup> Overall, the ratio of spending to after-tax income fell from 89 percent in 1972–1973 to 84 percent in 2003 and 79 percent in 2010. While the overall spending-to-income ratios fell between 1972–1973 and 2010, the ratio across income groups remained fairly constant. This occurs because of the increase in households at the higher end of the income distribution who have lower spending-to-income ratios. Based on aggregate trends in savings rates (which are decreasing during this period), the overall spending-to-income ratio should have been higher in the last two periods than in the first. However, figure 8.4 suggests that the differences in spending-to-income ratios occur across income groups at each point in time and have not changed over time.<sup>29</sup>

The ratios of total expenditure to after-tax incomes by income shown in figure 8.4 exhibit a dramatic pattern, and although there are some conceptual issues and systematic reporting errors with income taxes in the BLS tabulations, those sorts of corrections do not fundamentally change that pattern. The ratio of spending to income at low-income levels seems implau-

28. Each point on the chart marks average total expenditures divided by average after-tax income, at the value of after-tax income reported in the BLS tables. Values for average after-tax income in 1972–1973 and 2003 are inflated to 2010 dollars. The year 2003 marks the first year in which BLS published “high income” tables for the modern (post-1980) ongoing CE survey.

29. The stability of spending-to-income ratios across income groups also raises concerns about the approach used by Aguiar and Bils (2011) to “correct” for bias in studies that compare consumption versus income inequality. They use the 1972–1973 CE survey to estimate Engel curves, and impute missing spending in the 1980s based on those estimated relationships and an aggregate scaling factor. If underreporting for higher-income families was just as bad in the 1970s as it is today, then they are effectively just inflating observed spending to match aggregates.



**Fig. 8.4 Expenditure to after-tax income ratios in published CE data**

sibly high, and the ratio of spending to income at the top seems implausibly low. There are most likely problems with both income and expenditure reporting, and sorting households by income simply highlights those errors.

In any household survey there will be measurement error, and, given that the CE is focused on spending rather than income, it is not surprising that income may be poorly reported for some households.<sup>30</sup> The bottom of the income distribution includes many households who underreport income (e.g., the self-employed), and hence, the high ratios of expenditure to income at low incomes can be partially explained by the presence of these households. The argument that income is missing at the bottom is reinforced by a pragmatic view of lower-income households. It is impossible to spend twice your income (figure 8.4) if you have no assets to draw down and no access to credit, which is the basic conclusion one takes away from wealth surveys like the SCF or Panel Survey of Income Dynamics (PSID). Thus, except for students, households with temporary business losses, and retirees drawing

30. Indeed, the CE data includes a number of consumer units who either refuse to answer or say they “don’t know,” which is why income is imputed for a significant number of cases. The CE imputation procedures, described in Passero (2009) and Paulin and Ferraro (1996), focus on preserving the consumption-to-income relationship for those households who do participate, by using expenditures as an explanatory variable in the imputation procedures. The conclusions of this chapter might suggest some reconsideration of the current imputation procedures to reflect nonrandom nonresponse.

down assets, the high rates of implied dissaving by lower-income households in the CE are already implausible and proportional scaling-up of spending would only increase these already implausibly high spending-to-income ratios.

It is also unrealistic to think that families above \$100,000, on average, save the fraction of their disposable income implied by figure 8.4, using it for purchasing stocks, bonds, and other investments that are not captured by the CE. Such behavior would yield average wealth-to-income ratios for higher-income households that are much different than what we observe in wealth surveys (e.g., PSID and SCF).<sup>31</sup>

## 8.5 Conclusions

Only the very highest income households seem to be underrepresented in the CE Survey, but the overall underreported spending in the CE cannot be fully explained by that shortcoming. At least some of the shortfall in aggregate CE spending seems attributable to underreported spending by at least some CE respondents, and that has implications for research that relies on the relationship between spending and income in microdata. The observation that spending-to-income ratios fall with reported income in the CE implies that consumption-expenditure inequality will be less than income inequality, and the extent to which this ratio falls with income (and changes over time) has a dramatic impact on the estimated relationship between consumption expenditure and income inequality. Also, if this pattern in the spending-to-income ratios is partially due to measurement of total spending, then the amount of dissaving at low incomes and saving at high incomes will both be exaggerated and consumption taxes will appear (perhaps wrongly) to be highly regressive alternatives to income taxes.

Resolving whether expenditures are proportionally underreported for all CE respondents or disproportionately for higher-income (and thus higher-spending) respondents is a crucial task facing the current multiyear CE redesign effort (called Gemini). The mission of the Gemini project is to redesign the CE in order to improve data quality through a verifiable reduction in measurement error, with a particular focus on underreporting.<sup>32</sup>

31. Some might argue that these simple calculations ignore income fluctuations because households do not stay in the same income group from one year to the next. That is exactly the argument addressed by Sabelhaus and Groen (2000), who use data on income mobility from the PSID to test whether movements across income groups can explain the pattern of consumption to income in the CE. The answer they find is clearly no—there is not enough income mobility, even under the most extreme assumptions about consumption smoothing.

32. (For a description of the Gemini project, see <http://www.bls.gov/cex/geminiproject.htm>.) As part of this effort, the National Research Council, through its Committee on National Statistics (CNSTAT), has convened an expert panel to contribute to that planned redesign (see <http://www8.nationalacademies.org/cp/projectview.aspx?key=49322>).

Future research to examine this underreporting includes a joint effort by BLS and the Census Bureau is to examine additional variables, including income, in CE's nonresponse and calibration-adjustment processes.<sup>33</sup> This research will address a number of questions such as what variables are available for every household in the CE survey, both respondents and nonrespondents; what qualities characterize "good" variables for these procedures; and what variables other surveys use. An oversampling strategy such as that employed by the SCF may also be worth considering. Implementation of oversampling could be expensive, and it would not by itself address a bias problem, but if combined with revised methods for nonresponse adjustment it could be a valuable improvement. Finally, it may be the case that the demands placed on respondents in the current CE are simply too daunting because respondents are asked to remember several hundred spending items for each month in a three-month recall period. Hence, a third approach to reconciling the difference between incomes and spending across income groups might involve streamlining the collection of spending totals so that even high spenders will have a better chance to accurately estimate and report their total spending.<sup>34</sup> It is hoped that the results presented in this chapter will constitute a further contribution to the CE redesign program.

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33. In 2014, the CE will begin using a modified nonresponse adjustment that includes cells by income using the SOI public-use income data.

34. Browning and Crossley (2009) discuss the merits of collecting aggregated versus disaggregated spending data.

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