Improving the Measure of the Distribution of Personal Income

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Improving the measure of the distribution of Personal Income

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Abstract: Developing a national account based measure of the distribution of income from the commonly used Census based concept of money income has been the subject of earlier research—see Fixler and Johnson (2014) and Fixler, et al (2015) for example. A limitation of the earlier work is that the extrapolation from the survey data to the national account aggregate was based on "blow-up "factors that were constant across households. In this paper, we will explore using micro tax data to create income quintile specific blow up factors. More specifically, CPS data is linked to tax data by household in order to address misreporting and survey bias for several income categories. We find significant differences between the CPS and tax income for the same households, suggesting that simply replacing the survey income for the administrative income data is not satisfactory. Since the top incomes are significantly different, we create blow-up for the very top of the distribution, and recalculate distributional measures. Using these factors helps bridge the gap between micro data vs. macro statistics and also inform about results from other studies on aggregate income inequality, such as Piketty, Saez, and Zucman (2018).

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[1] Contact author, johnsods@umich.edu. We thank Andrew Craig for assistance in creating and evaluating the CPS and NIPA data. The views expressed in this research, including those related to statistical, methodological, technical, or operational issues, are solely those of the authors and do not necessarily reflect the official positions or policies of the Bureau of Economic Analysis or the University of Michigan, or the views of other staff members. The authors accept responsibility for all errors. This paper is released to inform interested parties of ongoing research and to encourage discussion of work in progress.

Introduction

With each release of GDP in the U.S., there are increasing stories about the impact on inequality and the distribution of growth. Before the July 2018 release, the Financial Times stated: "What's the matter with GDP?" and suggested that GDP is missing information about who gets the increase (Smith, July 2018). Interest has grown regarding the relationship between the distribution of growth and increase in inequality.

This disconnect between aggregate growth and its distribution has been amplified during the past few years, fueled by the Great Recession. The relationship between macroeconomic growth and income inequality has been the focus of many recent studies (see OECD, 2011; Boushey and Hersh, 2012; Boushey and Price, 2014; OECD, 2014). This view is echoed in recent *Economic Report of the President* and is the theme of the *Report by the Commission on the Measurement of Economic Performance and Social Progress* (Stiglitz, 2009).

Almost 70 years ago, Kuznets (1943) in his original report on the national accounts suggested that growth in GDP was not sufficient to evaluate social welfare. The recent rise in inequality, especially at the top of the distribution, has reinvigorated the effort to produce distributional measures. Recently Boushey and Clemens (2018) state: "The current one-number fits all approach of measuring GDP without distributional data supports the antiquated idea of 'growing the pie' without understanding where the pie goes." Led by the creation of the World Inequality Database and Piketty, Saez, and Zucman (2018), new efforts around the world have started to develop consistent measures of the distribution of the national accounts.

The OECD has created an international working group – Expert Group on Disparities in National Accounts-- who have created a handbook on methods, "Handbook on compiling distributional results on household income, consumption and saving consistent with national accounts." The goal of the handbook is to assist researchers and federal agencies in developing quality distributional results, which are comprehensive, consistent and comparable over time and cross countries. Furthermore, the Handbook will provide details for how these results have been derived, methods to assess the quality of the results, and help in understanding the differences between distributional results.

As Kuznets stressed in his development of the national accounts, a distribution of the national accounts is necessary to completely examine how economic growth, whose measures rely on national account statistics, is distributed. It is only by developing a measure of household income consistent with the national accounts that a complete measure of inequality can be produced. This is exactly the charge of the OECD group. The Handbook recommends using both survey and administrative data to create this distribution. Most measures of inequality use the household surveys, Census Bureau's Current Population Survey (CPS), The Federal Reserve's Survey of Consumer Finances (SCF), and so on. However, recent measures, like those of Piketty, Saez and Zucman (2016, 2018), use the tax record data.

In earlier work at the Bureau of Economic Analysis (Fixler and Johnson (2014) and Fixler et al. (2017)), we tried to develop a distribution of personal income using survey data. This paper uses data from both survey and tax records to assess whether the tax data can improve the measures at the top of the distribution, where much of the rise in inequality is believed to be taking place. As suggested in the Handbook and by Burkhauser et al. (2012), using administrative data to supplement survey data is hypothesized to significantly improve inequality measurement. We document the process of matching the CPS to the tax data, and focus on a comparison of the variables for which it is likely that the tax data are more informative; – wages, interest and dividends.[2] We find that there is a greater share of households with very high incomes present in the tax data as compared to the survey data. Accordingly, we adjust the survey data to reflect higher income households and estimate alternative measures of inequality. As expected, this adjustment inflates inequality measures compared to measures calculated using the internal CPS data alone.

Measuring Income

The next steps are to extend these efforts to impute the remaining income components of personal income, following Fixler et al. (2017) and to develop methods to create a supplemental sample of very high income households to append to the CPS, as in Jenkins (2017). Since, our adjustments increase the distribution at the top only slightly, one may need to impute new households at the top of the distribution. This procedure is used at the UK's Office of National Statistics (ONS, 2016) and discussed in Jenkins (2017). It is comparable to that used by Piketty, Saez, and Zucman (2018) (Hereafter, PSZ), who start with tax data and allocate the other components of national income. The increase in inequality can be seen in Figure 1A , which shows the share of income owned by the top 1% of the population using both the PSZ and Congressional Budget Office (CBO) methods. As one can see, this share has increased since 1979. The top 5% share from PSZ can be compared to the results of the BEA estimates from Fixler, Johnson, Furlong and Craig (2017) (hereafter, FJFC) in Figure 1B for 2000-2012. As one can see, the FJFC top 5% share is lower than the PSZ and does not increase as much between 2000 and 2012. However, much of the increase in the top 5% share is due to increases in the top 1% (as shown in the figure).

As with all comparisons of inequality measures, we must keep in mind that all of these measures use different definitions of income. However, PSZ use the NIPA concept of National Income and FJFC use Personal Income. The levels and trends of national and personal income are similar and their distributional properties should be fairly similar.[3]

Fixler and Johnson (2014) demonstrated that the aggregate level of CPS income is much less than the comparable income in the NIPA. Rothbaum (2015) recently provides a detailed

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[2] Since the tax data do not include all income components, we did not develop a comparable measure of money income.

[3] PSZ have calculated the top shares for personal income and their trends are similar.

comparison for each income source. Once the definition of income is controlled for, some of the remaining differences could be due to under-reporting in the CPS. Other differences may arise from the many high income individuals "missing" from the CPS. One suggestion for addressing this gap is to create an oversample similar to that done for the SCF.

If the source of the gap were entirely due to under-reporting, we could close the gap by substituting tax data for the income components of the CPS. Many researchers have attempted to match household survey data to tax or earnings records, see Burkhauser et al. (2017), Bollinger et al. (*forthcoming*), Rothbaum (2015), Bee, et al (2017), and Turek et al. (2012).

As stated by Fixler and Johnson (2014), "A more accurate method for adjusting for underreporting in the CPS would be to use the actual tax records data matched to the CPS." We are the first paper to match the CPS to the tax data and compare the universe in each. In this paper we show that the substitution of income tax variables for the CPS income variables is not a panacea for mis-reporting problems. The method follows that of Fixler and Johnson (2014) and FJFC (2017). Future work will attempt to use these adjustments to create an improved distribution of personal income from the national accounts.

Thus, the way forward may be to use the CPS and tax return data in combination, drawing on the CPS for sociodemographic variables and household composition and the tax data for income variables that cannot be obtained from the CPS, as well as for high income households not observed in the CPS. By using such mixed measures, we can improve macroeconomic analysis and provide data to examine how specific macroeconomic trends affect various household groups.[4]

There are a multitude of income measures used by researchers and the government. Fixler and Johnson (2014) compare income definitions (see Table 1). They show that there are many components of income that are included in the measures. Only three components are included in all income measures – employment income, investment income, and cash transfers from the government. The main differences in the income definitions are the treatment of imputed income, retirement income, capital gains (realized and unrealized), unrealized interest on property income and the inclusion of government and in-kind transfers. Even the Canberra definition, which is viewed as the standard in international comparisons, is different than the BEA definition, which follows the System of National Accounts (SNA).

[4] As the OECD EG-DNA expert group states, one of the main reasons to produce these distributional national accounts is "…to get a comprehensive and consistent view of the distribution of income, consumption and wealth, consistent with economy-wide totals. Whereas micro data sources usually focus on either income, consumption or wealth, the alignment to national accounts totals enables the combination of these flows and stocks in a coherent way, thus also providing the opportunity to derive consistent estimates on, for example, saving rates for various household groups. This is usually not possible on the basis of micro data, as the results on income, consumption and wealth are usually based on different underlying concepts, and may suffer from measurement and estimation errors, as a consequence of which the results are seldom coherent, often leading to incorrect or even conflicting results."

One of the main differences among the various definitions is the treatment of retirement income. Consider an elderly person with both a savings account and a defined contribution retirement account. The interest on these accounts will be counted as income in all measures. The regular withdrawal (or payment) will be included in two measures -- Haig-Simons and Canberra. If the person withdraws more money from his retirement accounts, this will be recorded as income only in the Haig-Simons, CBO, and Canberra measures.[5] Finally, if the retiree withdraws money from his or her savings account, this will only be included in Haig-Simons income because these savings withdrawals are actually decreases in net worth that will be spent.

Our ultimate goal, shown in FJFC, is to create a distribution for the US National Account concept of *Personal Income*, which is the income received by persons from participation in production, from government and business transfers, and from holding interest-bearing securities and corporate stocks. In addition, we eventually hope to develop a table comparable to the decomposition growth table that shows the annual growth rates of GDP and the distribution of these changes across the distribution of households according to personal income.

Personal Income (PI) also includes income received by nonprofit institutions serving households, by private non-insured welfare funds, and by private trust funds. It is natural to look at the PI income concept for decision making, especially for consumption. Most macro models use disposable PI in consumption function. PSZ, however, use National Income (NI) claiming: " [it is] in our view a more meaningful starting point, because it is internationally comparable, it is the aggregate used to compute macroeconomic growth, and it is comprehensive, including all forms of income that eventually accrue to individuals." PI and NI are fairly close in aggregate and trend. PI=NI –[corp. profits + taxes on production + contributions for gov. soc. ins. + net interest + bus. current transfer + current surplus of gov. enterp.] + [personal income receipts on assets + personal current transfer receipts].

In order to compare incomes across the data sets, we attempt to create a comparable income measure. The CPS money income measure is the most widely used, but it includes some components that will not be included in tax filings. The Federal tax data from the Statistics of Income (SOI) database includes a total income measure that includes the sum of the following items (excluding the reported interest and dividends of children): Wage and Salary, Total Interest (taxable and tax-exempt), Taxable Dividends, Alimony Received, Business Income, Pensions and Annuities, Net Rents, Royalties, Estates and Trusts, Farm Income, Unemployment Compensation, and Social Security Benefits. CPS Money Income also includes: Workers' Compensation, Public Assistance, Veterans' Payments, Survivor and Disability Benefits, Educational Assistance, Child Support, and miscellaneous financial assistance from outside of the household. These additional components comprise only about 3% of total money income,

[5] CBO simply uses a statistical match between CPS and tax data.

and hence, should not greatly impact the comparison. The tax data available in the matched file only contains a few of the detailed components of income. For this analysis, we focus on the total income, wages, interest and dividends.

Figure 2 shows that the distributions of CPS and tax data are fairly comparable. Tax records have more values at the lower end of the distribution and slightly more at the higher end. However, CPS values show no households with incomes over $2M, while in the SOI tables, there are households with incomes in excess of $10M. For example, in 2012 tax data, there are 13,000 tax filers with total Adjusted Gross Income (AGI) in excess of $10M. In the CPS, there is a $10M functional top code because of the survey instrument capacity. In the tax data, these households make up 4% of total AGI.

Data and Methods

The data used in our analysis are individual-level data from the internal Current Population Survey Annual Social and Economic Supplement (CPS ASEC) for survey years 2008-2013 (income years 2007-2012). These records are linked to Federal income tax data collected by the Internal Revenue Service (IRS) Form1040 records using a unique Protected Identification Key (PIK) produced within the Census Bureau's Center for Administrative Records Research and Applications. The PIK is a confidentiality-protected version of the Social Security Number (SSN). Since the Census does not currently ask respondents for a SSN, Census uses its own record linkage software system, the Person Validation System, to assign a SSN. This assignment relies on a probabilistic matching model based on name, address, date of birth, and gender. The SSN is then converted to a PIK in order to link the ASEC and the tax data. The Census Bureau changed its consent protocol to link respondents to administrative data beginning with the 2006 ASEC.[6]

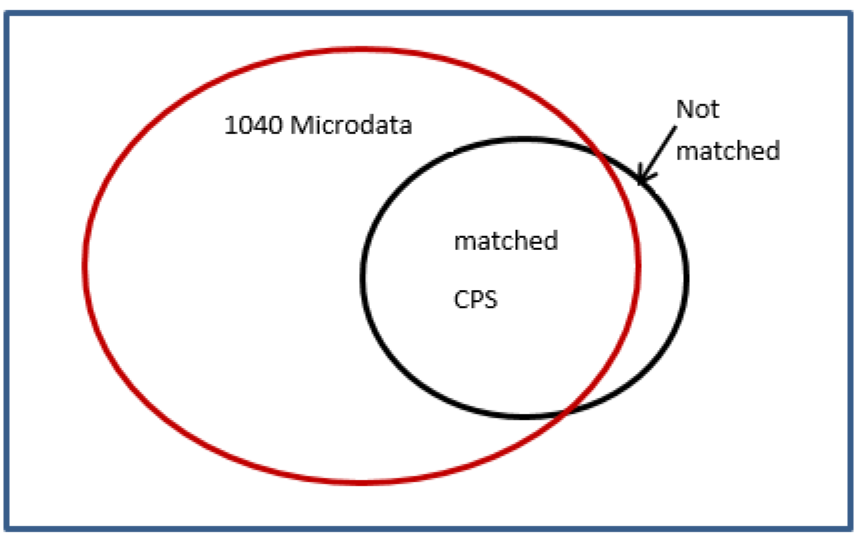
First, PIKs are assigned to records in the CPS ASEC and to records in the 1040 microdata through use of a crosswalk, matching CPS survey year to IRS filing year, e.g. a household surveyed in the CPS in 2013 reports 2012 earnings and a household filing a 1040 in 2013 is referencing 2012 earnings. The ASEC is specifically administered in March every year with tax preparation in mind in an effort to bolster accuracy of response to income questions.

The relevant variables from the 1040 microdata, which include wage income, dividend income, interest income, money income, adjusted gross income, and filing status (i.e., single or joint) are merged onto the CPS data by PIK. Note that taxable interest income and non-taxable interest income are summed to represent interest income.

[6] Respondents not wanting to be linked to administrative data had to notify the Census Bureau through the survey field representative, website or use a mail-in response in order to "opt-out". This opt-out rate is a very small 0.5 percent of the ASEC sample. If the respondent doesn't opt out, they are assigned a SSN using the Person Validation System.

Since we need to obtain household level income to compare to CPS, the values of each income source are added by household. Group quarters are omitted. If the records indicate a joint filing, a joint income variable is created. Where there are multiple PIKs corresponding to the same value for a joint filing, the record is only taken once for the household. For example, if person 1 and person 2 both have a value of 100 for money income and a joint filing status, the household receives an income of 100, rather than 200. If the records indicate a single filing, the person receives that value. Joint filings and single filings are then totaled by household to create an aggregate number for each household. This process is repeated for each income source. Additionally, each income source is bottom coded to 0. If a CPS record has been linked with a PIK but no value for a given income source for each member of the household, the household is assigned a value of 0 for that income source. Only households with at least one person with a PIK are kept. After all the income variables have been aggregated by household, the dataset is collapsed to a household level, about 70,000 observations per year. All values everywhere are nominal.

Using this procedure of matching the individuals from the tax records and the CPS yields match rates of about 93% in each year. Table 2 shows the rates for survey years 2008 and 2013 by income deciles. Similar to Bollinger et al. (*forthcoming)* the match rates increase with income. This suggests that there are more comparable households at the top of the distribution, and that those missing from our analysis are more likely to be at the bottom. One reason for this may be that some of those at the bottom of the distribution are less likely to file a tax return.



In the diagram, we see the three possible groups of households, those in the CPS who are matched to their 1040 data, those in the 1040 data who are not in the CPS, and those in the CPS who are not matched at all. To investigate those that potentially didn't match from the 1040 data, we compare wages, interest, and dividends of those that did match in the 1040 data with those that did not (i.e. those inside the red circle). For each of the income sources above, we constructed a factor by income source category (see more detail in next section) based on the comparison of the means. For example, if the mean of 1040 wages for those with wages greater than 1m was 2,507,000 for the unmatched and 2,195,000 for the matched, that would mean a factor of 2,507,000/2,195,000 = 1.14.

For the internal, unmerged CPS, the data is processed by aggregating up to a household level. Wages, interest, and dividends are individually bottom-coded to 0. Next, wages, interest, and dividends are multiplied by the "factors" (described above), in the following way: Wages are scaled if they are 1m+. Interest and Dividends are scaled if they are 100k+. Similar to FJFC, we compare a "money income" value, which is census money income (bottom-coded to 0) with a "scaled money income" value, which replaces the values for wages, interest, and dividends with their new values (multiplied by the factors), while keeping the other components of money income intact.[7] In the next section, we will explore how the distributional properties of this new distribution differ from the internal CPS.

Results

To begin our discussion, we first assess the differences between the CPS and the 1040 microdata by constructing a variety of comparisons in order to ascertain the usefulness of using administrative data to enhance survey data results. One of the key results is that there are major differences between what households report to the CPS and provide to the IRS. While some of these differences could be due to a match that is not accurate, given the high match rates, much of the difference is due to under- or over-reporting on the CPS.

Recalling the diagram above, in Figures 2 and 3), we compare the reported incomes for 2012 in the CPS and matched incomes for 2012 in the 1040 of those in the overlapping black and red circles. Figure 2 compares the distribution for the tax money income variable to the Census money income. Both income variables are bottom coded to 0. While the frequencies look similar, there are many more zeros in the tax data. If we remove the zeros (the first income category), the distributions are much closer. The distribution of the tax income variable is more left skewed, with more lower income values. However, for the top cells, there are more tax income values than Census income values. Figure 3 shows the means by income category. We note that the maximum number of tax money income is substantially larger than CPS, though the distributions are otherwise comparable. Figures 2A and 3A shows the same graphs for wages. The comparable results demonstrate that the discrepancy is not driven by other income sources.

[7] In FJFC a concept of "pseudo money income" was used. That concept included the subtraction of income variables that were not a part of PI.

Figure 4 shows the level difference for each household of “constructed income”, defined as the sum of the comparable income components (wages, interest, dividends, and social security) from both CPS and tax data for 2012. The difference is the tax income value less the comparable CPS value. Any households where the constructed income value was 0 were considered missing. If we compare wages instead in Figure 4A, we see the same pattern.

The implicit assumption in studies of income distribution is that the measured income in surveys can be improved by using tax data; the idea being that there are penalties for misreporting income on tax forms. However, as these figures demonstrate, there are large differences between the CPS reports and the IRS reports for the same income for the same household and the differences are not uniformly of one sign. The discrepancy is striking and violates a prior hypothesis that CPS income is consistently underreported. There is a substantial frequency of both positive and negative differences occurring at both the top and bottom end of the distributions.[8] Figure 4 shows that two-thirds of the households have a difference in incomes less than 20,000 in either direction. However, there are some large differences – 5% have values more different than 100,000. Figure 4A isolates the comparison to earnings (salaries and wages). Turek et al. (2012) also find large differences between the administrative earnings data (DER) and the CPS earnings data, which are similarly distributed on both sides (i.e., CPS>DER and DER>CPS).

We could hypothesize that looking at differences overall masks systematic differences at either end of the distribution. It could be supposed that CPS incomes are higher than tax incomes at the lower end and lower at the upper end. However, this is not the case. Figure 5 shows the same differences for 2012, but for the lowest quintile and highest quintile respectively. These show that it is not always the case that the CPS income is higher than tax income at the low end and lower than tax income at the high end. In the bottom quintile, only 30% of households have CPS income greater than tax income. For those in the top quintile, only 30% have tax income greater than in the CPS. In fact, there are a substantial number of households whose CPS is much higher than their tax income. These relationships hold for wages as well. This demonstrates that one cannot simply replace the CPS income with the tax income.

Accordingly, we return to our earlier discussion of those “missing” from the CPS. By comparing tax units that merged with the CPS with those that didn’t and considering their respective income distributions, we can determine whether the CPS sample is missing people (and households) at the top of the distribution. Figure 6 shows the distribution comparison. Similar to the CPS and tax income comparison (Figure 2), the non-matched has more lower income values. This is due to the lower match rates at the lower income levels. At the high income categories, there are more matched than non-matched, except for to top two categories. Hence, the main differnces

[8] It is important to keep in mind that the difference is for matched files and does not bear on the use of tax data to improve the representability of the upper part of the distribution.

are at the very top of the distribution. The non-matched show 0.31% over 1M, while the matched have only 0.18%. In addition, the mean income for the top category (over 1.5M) is 50% higher for the non-matched than the matched households.

Together, these results suggest that the CPS does not capture the very top of the distribution. This is similar to Burkhauser et al. (2012). While Bee et al. (2015) suggest that there are not differences in response rates for the high end of the distribution, they did not examine households within the top 5%.

As described in the methodology section, we can use these results to create factors, which are constructed using the ratio of the mean of the not-matched tax data/tax data matched to CPS for each income category. In this sense, we can obtain a picture of the different samples. Obviously the unmatched sample is very large. However, if the income distribution is different that could suggest that the CPS may have some under-reporting or missing observations when compared to the universe of the 1040 microdata. Table 3 shows the resulting factors for 2012.[9]

As we can see, the distributions of unmatched and matched tax data are very similar. The factors are significantly different from one in the lowest income category (as we discussed earlier) and in the highest for each factor. Given that there are no households with extremely large interest or dividends in the CPS, the factors are only applied to interest and dividend incomes greater than 100K. For wages, the factor of 1.14 is applied to incomes greater than 1M.

As described in the methodology section, once top wages, interest, and dividends have been multiplied by the factors above, total money income is recalculated ("scaled money income"). Tables 4 and 5 show the impacts on distributional measures for money income (internal cps) and scaled money income. The adjustments for top incomes slightly increases all three measures in Table 4– Gini, share of top 1% and share of top 5%. These adjustments also affect the change in the trends for incomes earned in 2007 and 2012, showing increasing inequality. Table 5 breaks the distribution into (weighted) quintiles.[10] Though, in real terms, mean income declined for all quintiles, it declined least for the top quintile, which is also the only quintile affected by this methodology.

An alternative method to create factors could be by ranking the distributions by total income. We found that there was so much re-ranking that the results depended on whether the distribution was ranked using CPS money income or tax income. Ranking by tax income and determining the ratio of tax income to CPS income yielded factors that were greater than one only in the top decile, with a factor of about 2 for the top percentile. However, tax income was below CPS income for the bottom 9 deciles. As a result, inequality would be increased, but it is

[9] They are nearly identical for 2007.

[10] It does not matter whether the quintiles are reconstructed or not for scaled money income because all the action is within the top 10% essentially, so they do not change.

not clear that these over-reports of income in the CPS should be ignored. Hokayem, et al. (2015) find the same results using wages from the detailed earnings records (DER) at SSA, which are basically the W-2 records that appear in the 1040. They develop a complicated imputation method to use both the CPS and DER information. Fixler and Johnson (2014) compared AGI in the CPS to the 1040 Microdata and found that the ratio between tax income and the CPS was also less than one until the 80th percentile (see Figure 8.5). They attempted to use the SOI aggregate data to adjust the CPS for top incomes. Again, because of the fact that the tax record data was lower than the CPS at the low income levels, the impact on inequality – both level and trend – was not significant.

Accordingly, with the results analyzed in this section, our next step is to use the new adjusted micro data to compute the other categories in personal income. This method would follow FJFC and use both CPS and CE incomes to impute the income components. With the top adjusted wages, interest and dividends, however, this should increase the shares at the top and bring our results closer to those in PSZ. As an example of this process, we consider the interest and imputed interest.

Adding Personal Income Imputed Interest to the distribution of Money Income

In moving from Census Money Income to Personal Income, the single largest component to add is imputed interest (See FJFC, Table 2). The category contains the imputed interest from financial institutions, insurance companies and owner occupied rent. The main hurdle is adjusting the CPS distribution so that the upper tail is more representative; as established above we know that the CPS is missing households at the upper end of the distribution.

More specifically, in the public use file, which we use for this step of the analysis, the small sample sizes in the CPS for the top two income brackets, 1.5m-2m and 2m+, lead to small sample weights and thus underreported population counts for these brackets. The SCF is known for over-sampling high income families, which leads to more representative population totals in the top tail of the distribution. For this analysis we adjust the weights in the CPS by taking the ratio of the SCF and CPS population totals for the top two income brackets. This ratio was multiplied by the CPS population total, in effect giving the SCF population. This new population total was divided by the CPS sample size for the two brackets to create a new household weight. Each household in the bracket then had the CPS weight replaced by the new adjusted weight. As a result, the number of households in the CPS population total increases by the difference of the sum of the top two bracket population totals for the SCF and CPS. As Figure 7 illustrates, in 2012 the CPS population totals for the 1.5m-2m and 2m+ brackets were 12,906 and 6,861 respectively and the overall population total was 122,459,424. The SCF population totals for the 1.5m-2m and 2m+ brackets were 79,145 and 187,528 respectively with an overall population total of 122,530,070. After we adjust the CPS weights to match those of the SCF, the overall population total for the CPS increases by (79,145 + 187,528) – (12,906 + 6,861) = 246,906. The new overall CPS population is therefore 122,459,424 + 246,906 = 122,706,330.

To allocate the PI imputed interest total, we use information from the CPS, SOI and SCF to determine the shares of income that come from interest. Those shares are based on nominal interest from financial instruments—bank accounts and bonds. We compute the interest income shares from each series in each income category, take the arithmetic mean and then use the mean to allocate the total imputed interest. Table 6 shows the distribution of interest income in the various surveys. The second column from the right shows that amount of imputed interest in PI and the far-right column shows the amount allocated to each household. For example, in 2012 imputed interest in PI is 598 billion dollars, and each household in the highest income category receives about 478,000 dollars.

Table 7 shows the impact of several adjustments. To begin we set the minimum CPS money income level equal to zero—the corresponding distribution is given in the far-left section of the table in each panel. The middle section shows the impact on CPS money income of applying the three factors discussed above. The impact is not great and essentially leaves the values for the upper tail unchanged. The far-right section shows the impact on the factor adjusted money income by the addition of imputed interest. The percent of households in the upper tail has gone up by an order of magnitude.

Table 8 presents the distributional aspects of the income measures presented in Table 7, except that in Table 8 the incomes are equivalized.[11] Some notable features of the table are: the addition of imputed interest greatly affects the means and medians at the upper tail; for all the categories, the mean is less than the median except for the top 0.1%; the means and medians within the top quintile are hugely different; and correspondingly the Gini coefficients increase.

Conclusion

This paper is part of a project to create a distribution for the US national account concept of Personal Income. We focus on two topics. First, we examine whether the substitution of Federal income tax data improves the survey-based measures of money income in the CPS. We find that the impact of this substitution is marginal; the differences between the money income using tax data and the collected money income is almost equally likely to be either positive or negative. Because this result focuses on the matched files in the CPS and the tax data, we turn to looking at the information in the unmatched tax data. More specifically we look at the ratio of unmatched to matched for three sources of income: wages, dividends and interest. We use these ratios (factors) to adjust the distribution of the money income for the upper tail—the part of the distribution for which the ratio only mattered—and find that again the change is marginal. This leads to the conclusion that there is not much to gain by matching the survey-based money income with the tax data. We did, however, confirm the well-known result that the CPS is not representative for the upper tail of the income distribution.

Second, using the factor-adjusted money income we moved toward the Personal Income measure

[11] Equivalization is done by dividing income by the square root of the number of members of the household.

by including imputed interest—the largest source of a difference between Personal Income and money income. Recognizing that imputed interest is likely more important at the upper tail, we first adjusted the upper tail of the CPS distribution using information in the SCF.   We then determined a distribution of interest income and then allocated imputed interest accordingly. We find that the addition of imputed greatly affects the upper tail—the mean and median for the top quintile is below that of the top 1% and 0.1% and the mean and medial for the former are substantially less than those of the former.   We then show that as expected the Gini rises.

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Tables and Figures

Table 1: Comparison of Income concepts

SOURCE	Haig/ Simons	Census	PI/NIPA (BEA)	CBO	SOI (AGI)	Canberra
Employment income	Yes	Yes	Yes	Yes	Yes	Yes
Employer contribution to Soc Sec	Yes	No	Yes	Yes	No	Yes
Employer-provided benefits[a]	Yes	No	Yes	Yes	No	Yes
Investment income	Yes	Yes	Yes .	Yes	Yes	Yes
Imputed investment income	Yes	No	Yes	No	No	No
Government cash transfers	Yes	Yes	Yes	Yes	Yes (taxable)	Yes
Employee contribution to Soc Sec	Yes	Yes	No (subtract)	Yes	Yes	Yes
Retirement income	Yes	Yes	No (only int.)	Yes	Yes	Yes
Cash assistance from others	Yes	Yes	No	Yes	No	Yes
Realized capital gains	Yes	No	No	Yes	Yes	No
Lump sum (IRA disbursements)	Yes	No	No	Yes	Taxable	Yes
In-kind government transfers[a]	Yes	No	Yes	Yes	No	No[b]
Other In-kind transfers[a]	Yes	No	No	No	No	No[b]
Home production	Yes	No	No	No	No	In concept
Imputed rent[a]	Yes	No	Yes	No	No	Yes
Unrealized capital gains	Yes	No	No	No	No	No
Savings withdrawals	Yes[c]	No	No	No	No	No

[a] Estimates are imputed in the CPS

[b] included in the final measure of disposable income

[c] included in the Haig-Simons equation; depletions in savings will simply increase consumption

Table 2: Linkage Rates of CPS ASEC to tax data by Money Income Decile

Linked Rate	2007	2012
Decile 1	86.4%	86.3%
Decile 2	89.3%	90.1%
Decile 3	90.3%	90.9%
Decile 4	91.7%	92.0%
Decile 5	92.2%	92.3%
Decile 6	93.1%	92.8%
Decile 7	93.4%	93.6%
Decile 8	94.7%	93.6%
Decile 9	95.0%	94.6%
Decile 10	94.8%	94.3%
Overall	**92.9%**	**92.5%**

Table 3: Tax Data Unmatched-Matched Factors (2012)

Wages		Interest		Dividends	
0-1k	0.846	0-1k	0.991	0-1k	0.947
1k-10k	1.022	1k-10k	1.015	1k-10k	1.024
10k-20k	1.000	10k-20k	0.978	10k-20k	1.003
20k-30k	0.997	20k-30k	0.992	20k-30k	0.998
30k-40k	0.999	30k-40k	0.994	30k-40k	0.997
40k-50k	0.999	40k-50k	1.005	40k-50k	0.994
50k-60k	0.999	50k-60k	0.984	50k-60k	1.001
60k-70k	0.999	60k-70k	1.002	60k-70k	0.999
70k-80k	1.001	70k-80k	1.002	70k-80k	1.010
80k-90k	1.000	80k-90k	1.010	80k-90k	*
90k-100k	1.000	90k-100k	1.008	90k-100k	*
100k-150k	1.003	100k-150k	1.010	100k-150k	1.021
150k-200k	1.001	150k+	2.940	150k+	1.377
200k-250k	0.997				
250k-300k	0.998				
300k-500k	1.005				
500k-1m	0.998				
1m+	1.142				

* indicates there were too few observations to report this factor

Table 4: Scaled vs. Unscaled Distribution Results

	2007		2012		2007-2012	
	Unscaled	Scaled	Unscaled	Scaled	%Δ Unscaled	%Δ Scaled
Top 1% Share	0.122	0.124	0.130	0.136	7.2%	8.9%
Top 5% Share	0.238	0.240	0.249	0.254	4.8%	5.7%
Gini	0.463	0.465	0.477	0.480	3.1%	3.4%
N	**76,000**	**76,000**	**75,000**	**75,000**		

Table 5: Scaled vs. Unscaled Quintiles

	2007		2012 (deflated)		2007-2012 (deflated)	
Quintile	Unscaled	Scaled	Unscaled	Scaled	%Δ Unscaled	%Δ Scaled
0-20%	11560	11560	10150	10150	-12.2%	-12.2%
20-40%	29450	29450	26191	26191	-11.1%	-11.1%
40-60%	49980	49980	45133	45133	-9.7%	-9.7%
60-80%	79210	79210	72400	72400	-8.6%	-8.6%
80-100%	168300	169300	160410	162350	-4.7%	-4.1%

Table 6: A Comparison of Interest Distributions by Income Bracket

2007	CPS			SCF			SOI			Arith. Mean of Share	Imputed Interest (Billions)	Allocated Impt. Int. Value
Income Bracket	Population	Amount (M)	Share	Population	Amount (M)	Share	Population	Amount (M)	Share			
$0	1,470,583	4.1	0.0%	473,934	1,484.4	0.8%	1,907,835	9,179.0	2.6%	1.1%	5.5	3,767
1-10k	6,984,844	675.8	0.3%	7,351,360	263.7	0.1%	24,045,493	4,785.7	1.4%	0.6%	2.9	418
10-20k	13,778,823	3,330.5	1.4%	15,422,830	1,566.0	0.8%	22,976,467	11,038.8	3.2%	1.8%	8.7	633
20-30k	13,114,622	6,456.6	2.7%	15,147,642	4,270.0	2.2%	18,969,031	10,710.6	3.1%	2.6%	12.9	985
30-40k	12,014,860	8,058.9	3.3%	13,270,849	4,447.4	2.3%	14,740,806	11,301.9	3.3%	2.9%	14.4	1,201
40-50k	10,719,390	9,099.7	3.8%	10,774,324	3,356.0	1.7%	11,150,798	10,536.5	3.0%	2.8%	13.9	1,294
50-75k	21,230,226	25,055.8	10.4%	20,126,294	10,135.3	5.1%	19,450,744	29,710.3	8.6%	8.0%	39.3	1,849
75-100k	13,796,516	27,475.1	11.4%	12,023,315	13,300.3	6.8%	11,744,132	26,427.3	7.6%	8.6%	42.0	3,042
100-200k	19,374,133	96,533.6	40.0%	15,553,917	29,636.5	15.1%	13,457,876	54,275.5	15.6%	23.5%	115.2	5,945
200-500k	3,872,172	57,144.3	23.7%	4,343,757	32,199.6	16.4%	3,492,353	47,803.1	13.8%	17.9%	87.7	22,642
500k-1m	289,819	5,858.0	2.4%	959,512	23,755.7	12.1%	651,049	25,865.2	7.4%	7.3%	35.8	123,392
1m-1.5m	135,000	1,695.1	0.7%	301,455	16,037.8	8.1%	166,362	13,516.1	3.9%	4.2%	20.8	153,819
1.5m-2m	126,615*	59.5	0.0%	126,615	12,112.3	6.2%	70,733	8,577.9	2.5%	2.9%	14.1	111,313
2m+	231,837**	32.9	0.0%	231,837	44,350.2	22.5%	155,125	83,681.8	24.1%	15.5%	76.0	327,868
Total	117,139,441	241,480.1		116,107,641	196,915.1		142,978,804	347,409.5		100.0%	489.1	
2012	CPS			SCF			SOI			Arith. Mean of Share	Imputed Interest (Billions)	Allocated Impt. Int. Value
Income Bracket	Population	Amount (M)	Share	Population	Amount (M)	Share	Population	Amount (M)	Share			
$0	1,896,292	15.0	0.0%	434,777	3,392.5	2.2%	2,128,548	7.8	4.3%	2.2%	12.6	6,640
1-10k	7,036,985	536.5	0.4%	5,383,875	289.7	0.2%	22,336,318	2.8	1.6%	0.7%	4.1	577
10-20k	14,139,168	1,838.2	1.2%	17,628,149	1,508.6	1.0%	24,247,770	5.0	2.7%	1.6%	9.6	678
20-30k	13,871,650	3,218.7	2.1%	16,046,110	2,075.9	1.3%	18,903,110	5.0	2.7%	2.1%	12.1	870
30-40k	12,171,920	4,230.5	2.8%	14,675,884	1,683.8	1.1%	14,451,152	4.7	2.5%	2.2%	12.5	1,028
40-50k	10,827,870	5,273.1	3.5%	11,566,124	1,870.4	1.2%	10,873,672	5.2	2.9%	2.5%	14.7	1,357
50-75k	21,397,647	15,546.9	10.4%	19,894,966	4,459.1	2.9%	18,985,371	12.9	7.0%	6.8%	39.3	1,839
75-100k	14,277,209	16,673.7	11.1%	12,314,149	6,441.2	4.2%	12,103,891	11.5	6.3%	7.2%	41.8	2,929
100-200k	21,368,060	58,739.8	39.2%	17,238,928	24,711.4	16.1%	15,646,648	26.8	14.6%	23.3%	135.4	6,336
200-500k	4,879,662	39,071.9	26.1%	5,435,720	38,515.5	25.0%	4,154,112	26.6	14.6%	21.9%	127.2	26,065
500k-1m	387,185	3,129.1	2.1%	1,248,706	15,598.9	10.1%	705,029	15.8	8.6%	6.9%	40.4	104,251
1m-1.5m	186,008	1,188.3	0.8%	396,009	12,134.0	7.9%	169,413	7.5	4.1%	4.3%	24.7	132,849
1.5m-2m	79,145*	73.7	0.0%	79,145	9,181.9	6.0%	71,874	5.2	2.8%	2.9%	17.1	216,280
2m+	187,528**	282.3	0.2%	187,528	32,050.8	20.8%	151,563	46.2	25.3%	15.4%	89.7	478,067
Total	122,706,330	149,817.8		122,530,070	153,913.7		144,928,471	182.9		100.0%	581.1	

Table 7: Adjustments to CPS Money Income

2007	CPS Money Income (Min. Income = 0)				CPS Money Income (3 Adjustment Factors)				CPS Money Inc (3 Adj. Factors + Imputed Int.)			
Income	Mean	Median	# of Hh	% of Hh	Mean	Median	# of Hh	% of Hh	Mean	Median	# of Hh	% of Hh
$0	0	0	1,470,583	1.3%	0	0	1,470,583	1.3%	*NA*	*NA*	*NA*	*NA*
1-10k	6,332	7,200	6,984,844	6.0%	6,332	7,200	6,984,844	6.0%	6,016	6,418	8,015,216	6.8%
10-20k	14,756	14,798	13,778,823	11.8%	14,756	14,798	13,778,823	11.8%	15,030	15,033	13,687,422	11.7%
20-30k	24,549	24,732	13,114,622	11.2%	24,549	24,732	13,114,622	11.2%	25,019	25,001	12,864,993	11.0%
30-40k	34,447	34,654	12,014,860	10.3%	34,447	34,654	12,014,860	10.3%	34,834	34,867	11,670,730	10.0%
40-50k	44,342	44,400	10,719,390	9.2%	44,342	44,400	10,719,390	9.2%	44,666	44,464	10,877,364	9.3%
50-75k	61,082	60,347	21,230,226	18.2%	61,082	60,347	21,230,226	18.2%	61,759	61,849	21,203,570	18.1%
75-100k	86,011	85,390	13,796,516	11.8%	86,011	85,390	13,796,516	11.8%	86,984	86,864	13,569,848	11.6%
100-200k	132,531	126,362	19,374,133	16.6%	132,519	126,355	19,367,949	16.6%	135,188	129,335	20,261,989	17.3%
200-500k	267,530	243,950	3,872,172	3.3%	267,092	243,312	3,823,955	3.3%	280,688	259,642	4,111,259	3.5%
500k-1m	654,024	622,730	289,819	0.2%	664,092	649,999	340,654	0.3%	721,214	706,636	353,337	0.3%
1m-1.5m	1,126,327	1,128,999	135,000	0.1%	1,269,060	1,289,138	136,207	0.1%	1,335,228	1,410,018	140,431	0.1%
1.5m-2m	1,914,619	1,914,619	1,488	0.001%	1,593,478	1,610,219	2,359	0.002%	1,545,099	1,522,706	24,831	0.0%
2m+	2,235,704	2,235,704	1,020	0.001%	2,329,578	2,179,676	2,507	0.002%	2,669,431	2,876,113	358,452	0.3%
All	67,582	50,000	116,783,496	100%	67,979	50,000	116,783,496	100%	79,297	51,849	117,139,441	100%
2012	CPS Money Income (Min. Income = 0)				CPS Money Income (3 Adjustment Factors)				CPS Money Inc (3 Adj. Factors + Imputed Int.)			
Income	Mean	Median	# of Hh	% of Hh	Mean	Median	# of Hh	% of Hh	Mean	Median	# of Hh	% of Hh
$0	0	0	1,896,292	1.5%	0	0	1,896,292	1.5%	*NA*	*NA*	*NA*	*NA*
1-10k	6,118	7,000	7,036,985	5.7%	6,118	7,000	7,036,985	5.7%	6,249	6,640	7,970,318	6.5%
10-20k	14,870	15,000	14,139,168	11.5%	14,870	15,000	14,139,168	11.5%	14,973	15,077	14,430,278	11.8%
20-30k	24,642	24,799	13,871,650	11.3%	24,642	24,799	13,871,650	11.3%	24,966	24,906	13,730,576	11.2%
30-40k	34,457	34,636	12,171,920	9.9%	34,457	34,636	12,171,920	9.9%	34,798	34,959	12,122,472	9.9%
40-50k	44,529	44,710	10,827,870	8.8%	44,529	44,710	10,827,870	8.8%	44,919	44,943	10,533,782	8.6%
50-75k	61,286	60,652	21,397,647	17.5%	61,286	60,652	21,397,647	17.5%	61,853	61,839	21,540,652	17.6%
75-100k	85,941	85,200	14,277,209	11.7%	85,941	85,200	14,277,209	11.7%	87,006	86,649	14,224,753	11.6%
100-200k	134,521	129,356	21,368,060	17.4%	134,518	129,354	21,363,779	17.4%	137,656	132,486	21,974,793	17.9%
200-500k	268,908	245,965	4,879,662	4.0%	269,026	246,000	4,844,432	4.0%	284,933	264,269	5,247,593	4.3%
500k-1m	649,285	610,842	387,185	0.3%	656,743	623,370	424,377	0.3%	707,140	689,981	446,497	0.4%
1m-1.5m	1,136,633	1,119,169	186,008	0.2%	1,269,019	1,265,909	185,703	0.2%	1,330,749	1,390,174	196,015	0.2%
1.5m-2m	1,721,474	1,849,999	12,906	0.01%	1,714,275	1,730,911	10,435	0.01%	1,814,904	1,929,921	61,500	0.1%
2m+	2,388,590	2,671,368	6,861	0.01%	2,456,981	2,306,137	11,958	0.01%	3,051,359	2,877,266	227,101	0.2%
All	71,233	50,340	122,459,424	100%	71,647	50,340	122,459,424	100%	81,292	52,339	122,706,330	100%

Table 8: Distributional Aspects of Income Measures (Equivalized)

	2007			2012		
	CPS Money Income (Min. Income = 0)	CPS Money Income (3 Adj. Factors)	CPS Money Income (3 Adj. Factors + Imputed Interest)	CPS Money Income (Min. Income = 0)	CPS Money Income (3 Adj. Factors)	CPS Money Income (3 Adj. Factors + Imputed Interest)
Mean_All	44,149	44,402	46,639	46,587	46,859	49,416
Mean_Q1	8,958	8,958	9,575	8,788	8,788	9,653
Mean_Q2	20,961	20,961	21,726	21,282	21,282	21,981
Mean_Q3	33,545	33,545	34,647	34,815	34,815	35,920
Mean_Q4	50,171	50,171	52,045	53,120	53,120	55,160
Mean_Q5	105,066	106,284	113,118	114,196	115,534	123,646
Top 1%	332,232	354,776	579,832	392,670	416,277	667,199
Top .1%	757,804	863,517	1,225,490	907,615	1,019,169	1,538,322
Median_All	33,461	33,461	34,453	34,641	34,641	35,703
Median_Q1	9,680	9,680	10,071	9,600	9,600	10,153
Median_Q2	20,882	20,882	21,655	21,204	21,204	21,940
Median_Q3	33,362	33,362	34,404	34,788	34,788	35,818
Median_Q4	49,845	49,845	51,512	52,400	52,400	54,418
Median_Q5	84,870	84,870	88,620	90,802	90,802	94,969
Top 1%	255,565	263,044	357,582	304,203	314,898	406,288
Top .1%	703,040	794,087	1,438,056	812,676	914,277	1,386,913
Gini	0.442	0.445	0.486	0.456	0.459	0.496

Figure 1a: A Comparison of the Top 1% Share (Piketty, Saez, and Zucman (2018) vs. Congressional Budget Office)

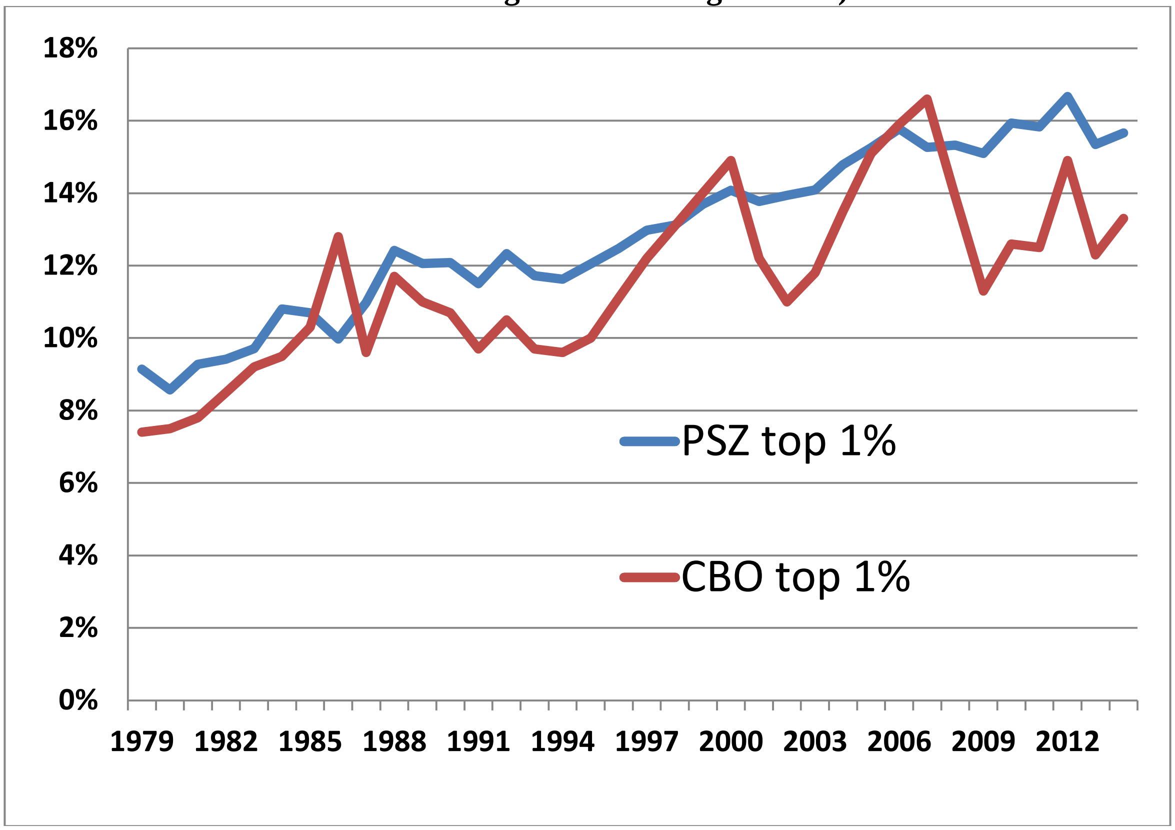

Figure 1b: Comparison of Top Shares

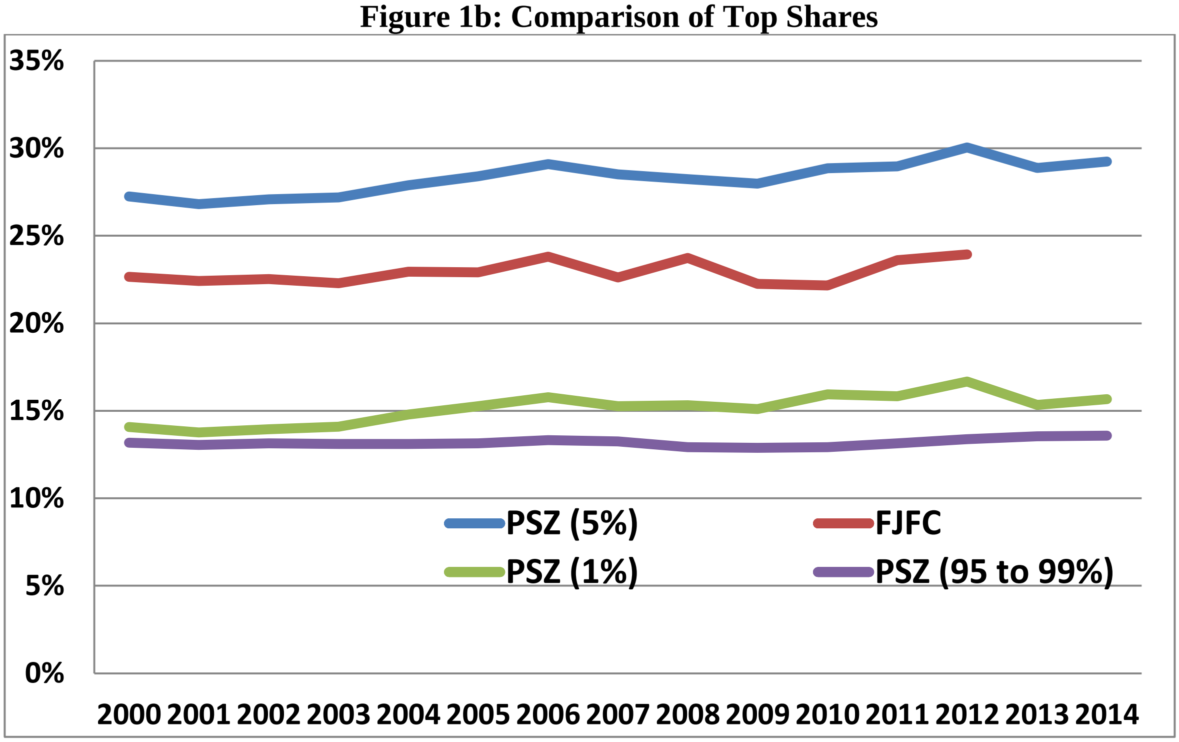

Figure 2: Comparing CPS Money Income & Tax Money Income

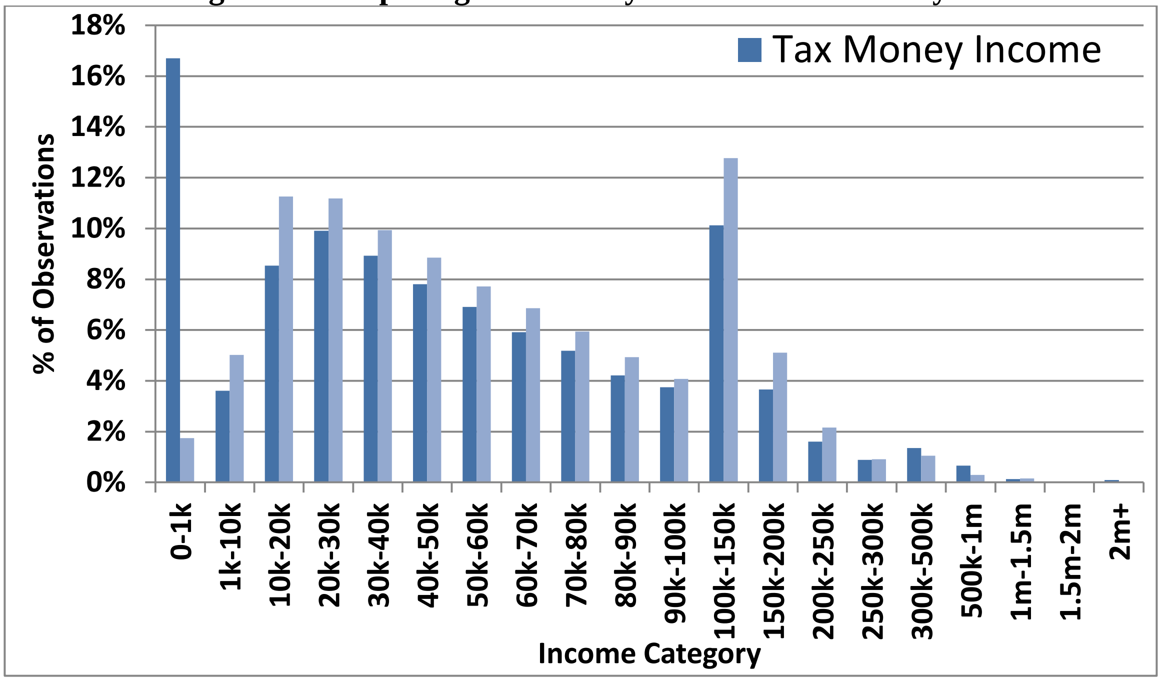

Figure 2A: Comparing CPS Wage & Tax Wage

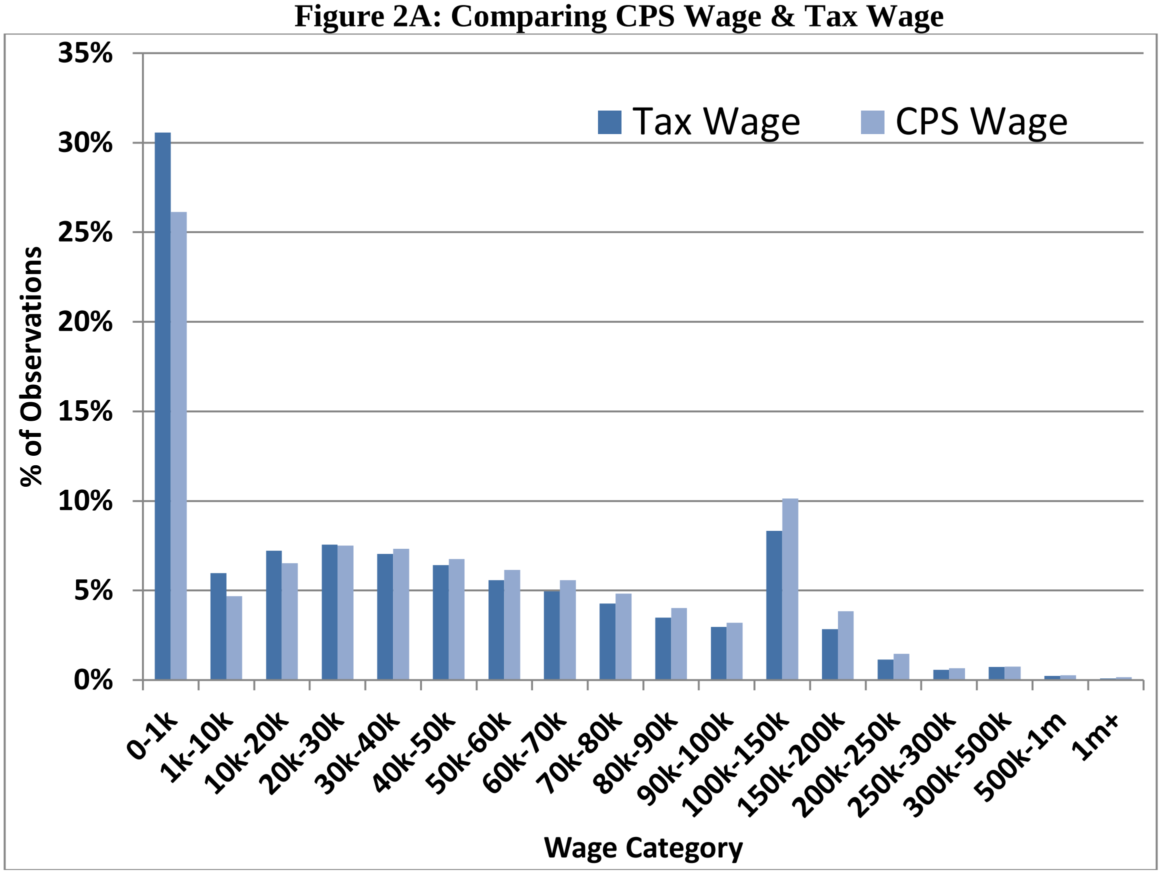

Figure 3: Mean Incomes by Income Category (Matched CPS)

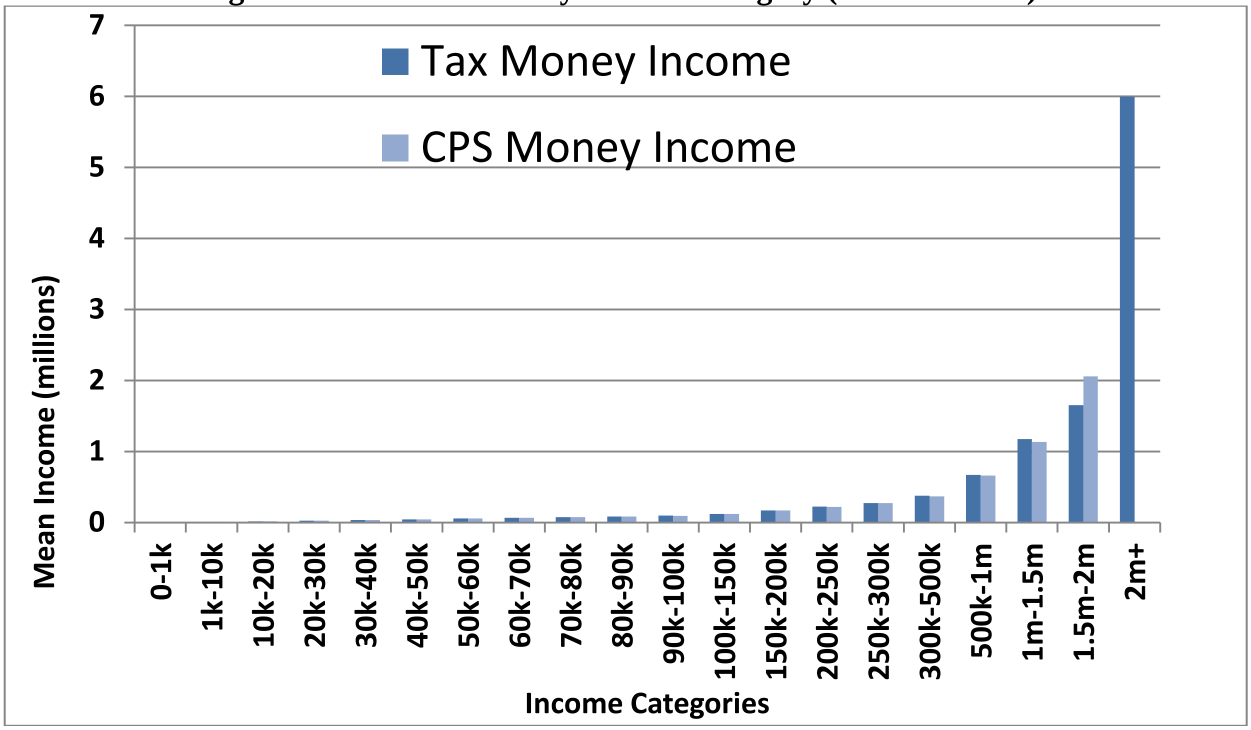

Figure 3A: Comparing Means of CPS Wage & Tax Wage

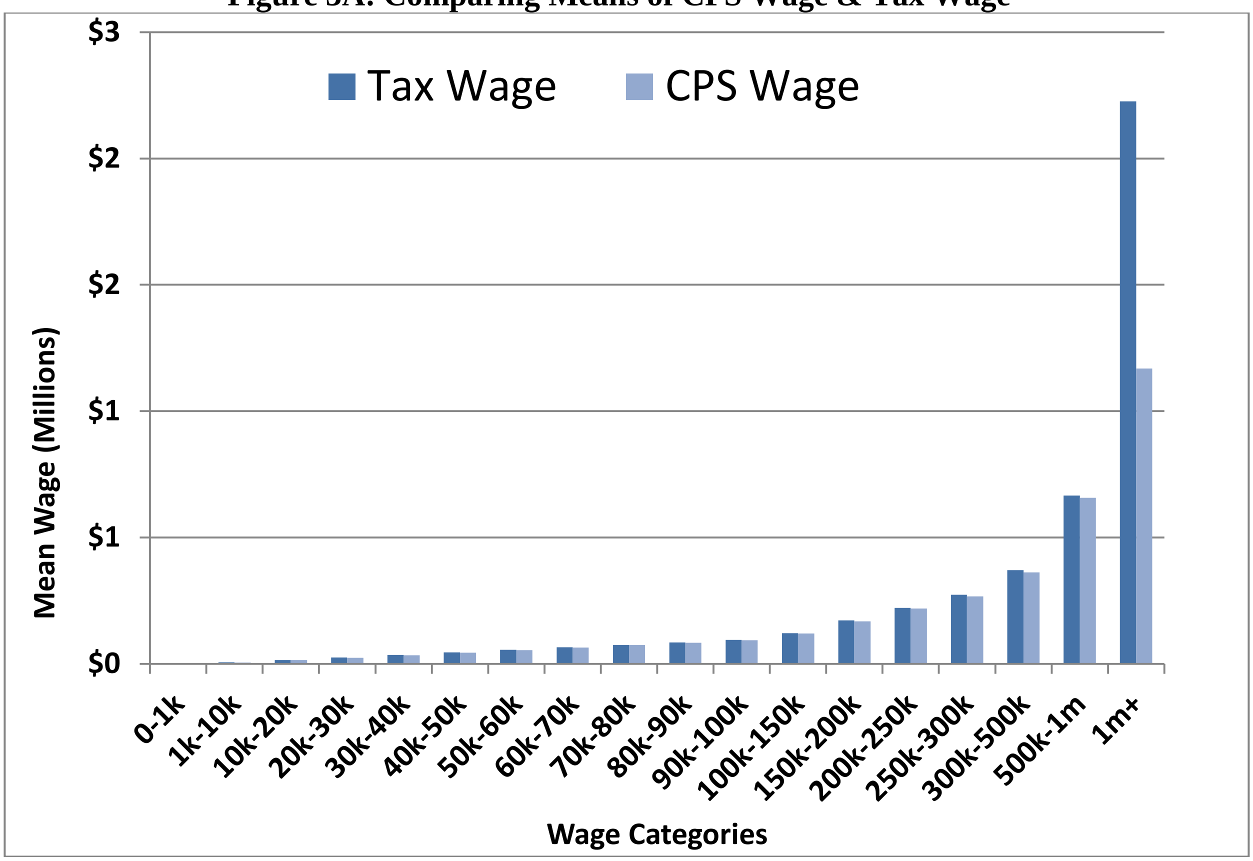

Figure 4: Level Difference in Constructed Income (Tax-CPS)

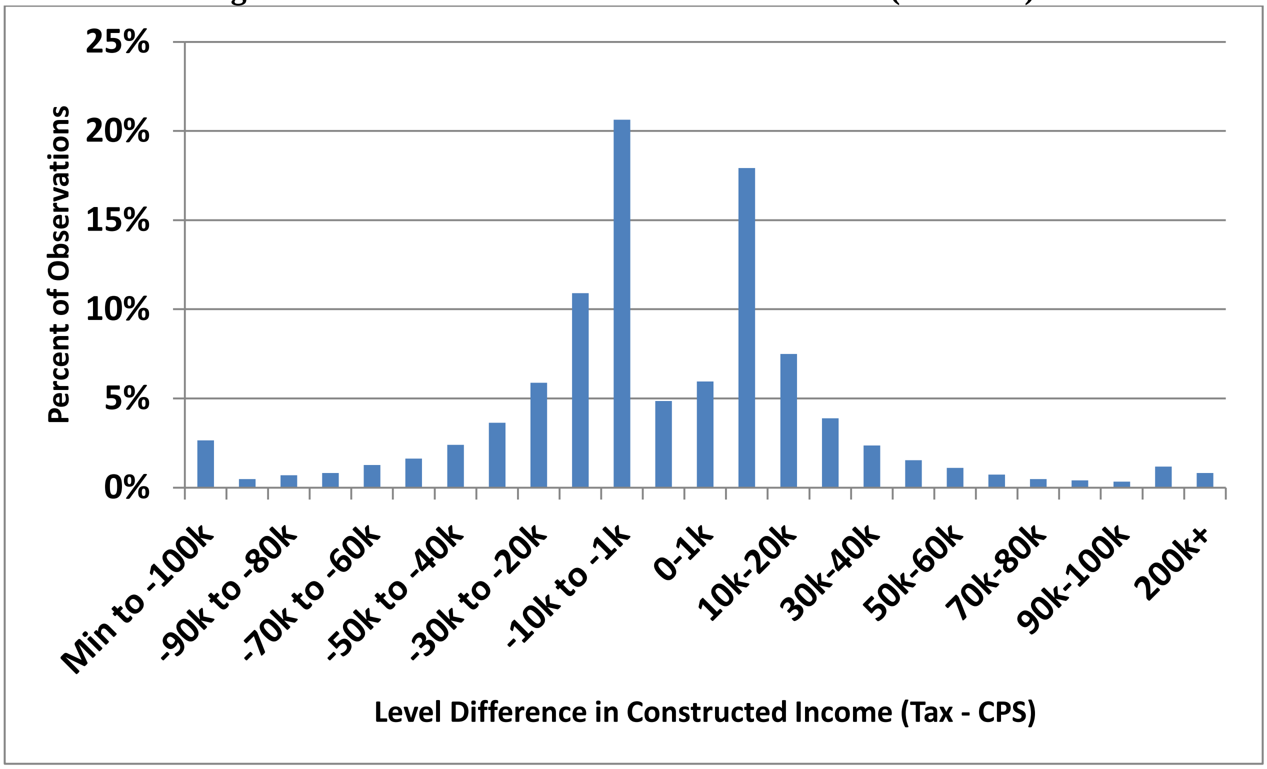

Figure 4A: Level Difference in Wage

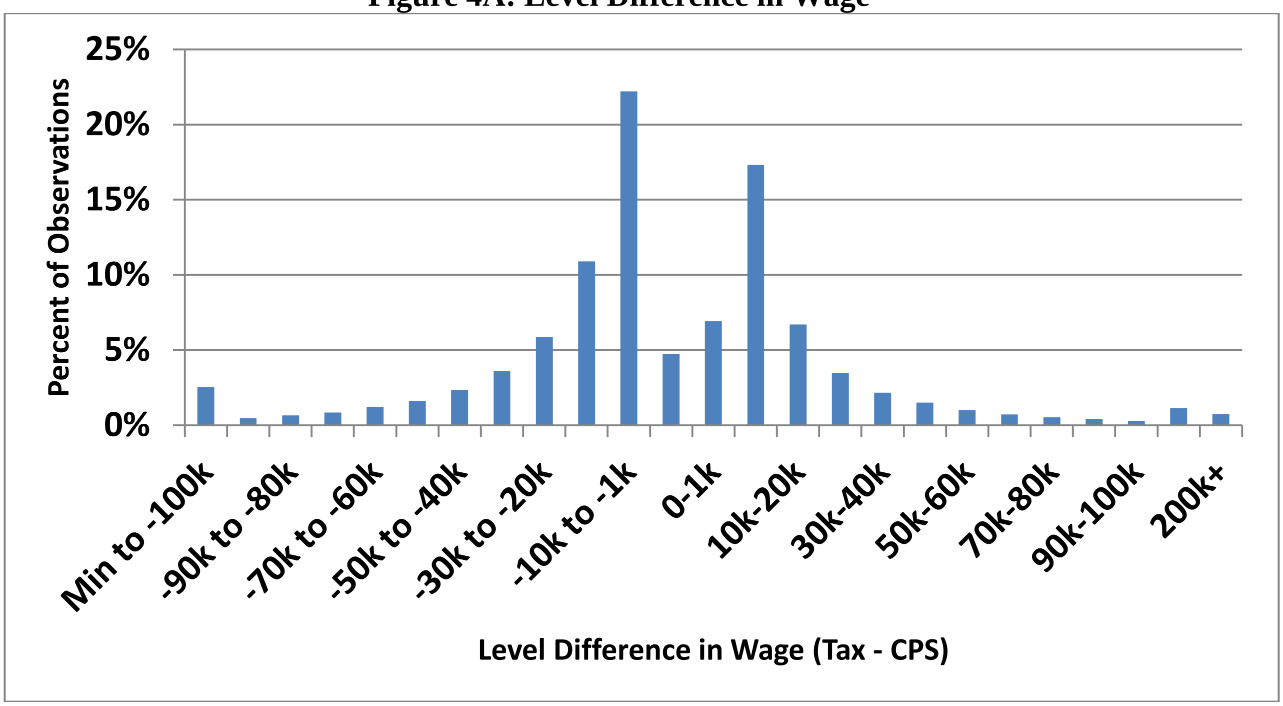

Figure 5: Level Difference for Income by Quintiles

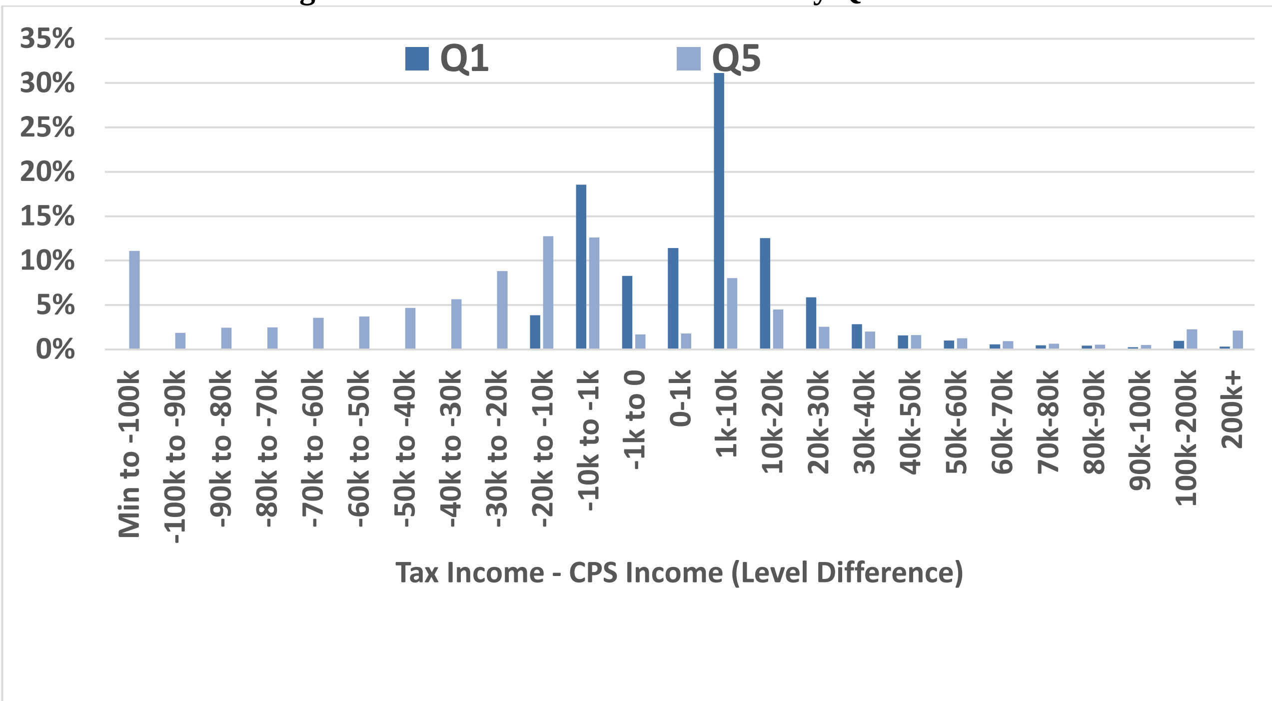

Figure 6: Compare unmatched tax data to matched tax data

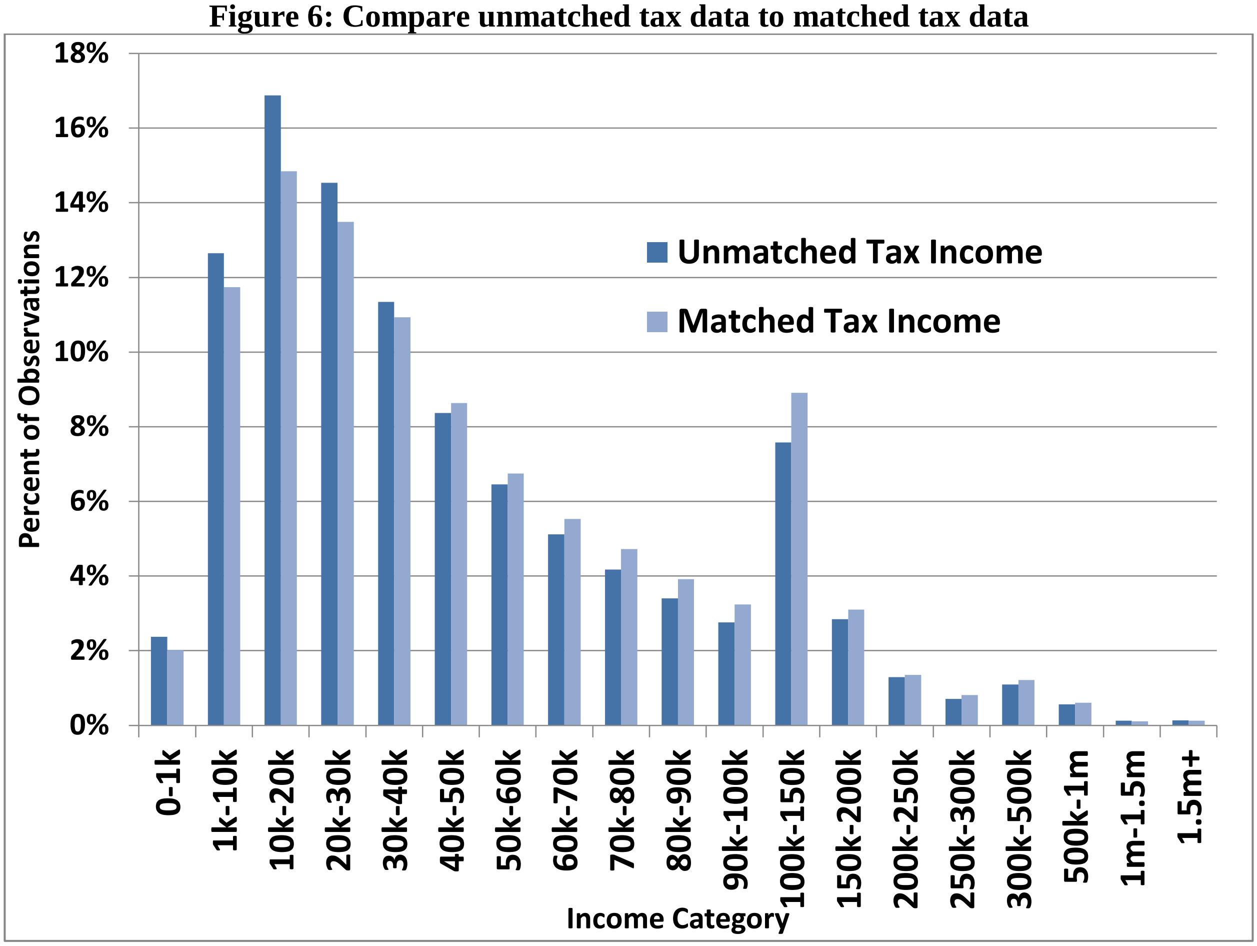

Figure 7: CPS Weights and SCF Weights Incorporated in Top 2 Income Categories