Recent Trends in Top Income Shares in the USA:
Reconciling Estimates from March CPS and IRS Tax Return Data

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Abstract

Although most research on US income inequality trends is based on public-use March CPS data, a new wave of research using IRS tax return data reports substantially higher levels of inequality and faster growing trends for recent years. We show that these apparently inconsistent estimates are largely reconciled when the income distribution and inequality are defined in the same way. Using internal CPS data for 1967–2006, we show that estimates of top income shares based on internal CPS data for 1967–2006 are similar in many respects to the IRS data-based estimates reported by Piketty and Saez (2003). Our results imply that changes in US income inequality since 1993 are largely driven by changes in the share of the top 1 percent.

Key Words: US Income Inequality, Top income shares, March CPS, IRS tax return data

JEL Classifications: D31, C81

Introduction

The March Current Population Survey (CPS) public-use files have been the primary data source used to study income inequality trends in the USA.[1] The consensus finding of research based on these data is that household income inequality increased substantially in the 1970s and 1980s, and continued to increase but at a much slower pace starting in the 1990s (Gottschalk and Danziger 2005, Daly and Valetta 2006, and Burkhauser, Feng, and Jenkins 2009).

The most notable alternative source for studying income inequality trends derives from tax return data. In their seminal paper, Piketty and Saez (2003) use data from Internal Revenue Service (IRS) Statistics of Income tax returns to analyze income inequality trends in the USA. Their paper was one of the first in a growing literature that has used tax return data to examine income inequality trends around the world. See Piketty (2003) for France, Atkinson (2005) for the UK, Saez and Vaell (2005) for Canada, Bach, Corneo and Steiner (2009) for Germany, Dell (2005) for Germany and Switzerland, and Atkinson and Leigh (2007) for Australia. Atkinson and Piketty (2007), Atkinson, Piketty and Saez (forthcoming), and Leigh (2009) provide comprehensive reviews of this literature**.**

One of Piketty and Saez's major contributions derives from being able to observe income inequality trends over a much longer period than previous researchers: tax return data are available for years well before any survey data on income was collected. However, their findings have also sparked debate about inequality trends in recent years. For a flavor of the debate on this topic, see the blog postings by leading economists and others on the Economists View website (2007). Reynolds (2007) provides an illustration of how the work by Piketty and Saez has altered the popular view of recent trends in income inequality and a critique of their results.

In contrast to research based on CPS data that finds income inequality slowing in the

1990s, Piketty and Saez (2003, 2008) find that the share of total income held by the very richest groups grew during the 1990s and, with the exception of the period from 2000–2002, continued to rise rapidly through the beginning of the 21st century as well. What explains the differences in inequality trends found by researchers using these two types of data?

One explanation is that there are deficiencies in one or both of these data sets that limit researchers' abilities to observe the true trends in inequality. Critics of using the public-use CPS to measure income inequality argue that topcoding, undercoverage, and underreporting of top incomes restrict the survey's ability to observe income changes for those at the top of the distribution. See inter alia Levy and Murnane (1992), Slemrod (1996), Burkhauser, Couch, Houtenville and Rovba (2003–2004), Piketty and Saez (2006*b*), and Burkhauser, Feng, and Jenkins (2009). Thus, to the extent that income inequality changes are due to changes in the topcoded portion of the CPS, researchers using this data may mismeasure trends in income inequality.

Using IRS data to measure income inequality also has potential limitations, however. Critics point out that tax filers have a financial incentive to report their income in ways that limit their tax liabilities and, as a result, filing behavior is sensitive to changes in the personal income tax rate. There are several fiscal manipulation strategies that are sensitive to changes in marginal tax rates and income reporting rules. These include reclassifying income as either wage earnings or business profits depending on which is taxed less (Sivadasan and Slemrod 2008), receiving untaxed fringe benefits in lieu of wage compensation (Woodbury and Hammermesh 1992), or deferring compensation through stock options or deferred compensation packages (Scholes and Wolfson 1992, Goolsbee 2000). Since high income earners are most able to adjust the way that they receive and report income, tax return data may especially not be able to capture income at the top of the distribution accurately. For example, Slemrod (1995) suggests that tax law changes since the 1970s have provided incentives for the very rich to switch their reported income from Subchapter-C corporation profits, which are not reported on personal income tax forms, to S-corporation profits and personal wage income, which are reported. This, in turn, may lead researchers using tax return data to overstate the actual rise in income among the very rich. See Feenberg and Poterba (1993) for an earlier discussion of this problem and a summary of the difficulties measuring top incomes with tax records data.

Piketty and Saez (2003) acknowledge that this type of fiscal manipulation may affect measures of top income shares, but argue that such effects are problematic only for short-term trends rather than the long run trends in income inequality which are their primary concern. However, for researchers interested in the relatively short-term trends in income inequality of recent years, time-shifting of income may still pose a problem. Additionally, while time-shifting of income may only impact income inequality in the short-term, income that is received in ways other than through labor earnings – such as through higher non-taxable fringe benefits or the reporting of wage earnings as business profits – will never be reported on personal income tax forms and thus could have implications for long-term inequality trends. Thus, to the extent that changes in reporting rules alter the way income is reported at the top of the distribution, researchers using IRS tax return data may mismeasure actual changes in income inequality.

Yet another potential explanation for the differences in estimated inequality trends is that they result from differences in the definition of income and how its distribution is summarized rather than differences in the data sources themselves. Although all researchers using public-use CPS data or IRS tax data examine “inequality” in the broad sense, there are substantial differences in their definitions of “income” (the sources included – most especially the inclusion of government transfers and non-taxable income in the former and its exclusion in the latter – and whether there is adjustment for differences in "needs"), the income recipient unit (tax units versus households and individuals within them), and how best to measure inequality (in terms of top income shares versus a more comprehensive measure such as the Gini coefficient).

To some extent, these differences in practice have evolved because of the nature of the data examined. For example, researchers using public-use CPS data, which has a high prevalence of topcoded values at the top of the income distribution, often measure inequality using the ratio of the 90th percentile to the 10th percentile ("p90/p10") to mitigate problems arising from topcoding. (See Burkhauser, Feng, and Jenkins 2009 for a discussion of the limitations of this measure, with CPS illustrations.) Researchers using tax return data focus on top income shares since many low income individuals do not file a tax return. So it is not possible to directly derive measures of income inequality that directly take account of the income of poorer groups (Piketty and Saez 2006*a*). To date, no researchers have attempted to bridge the gap between the CPS- and IRS-based literatures to determine the extent to which the differences in inequality estimates emanating from these two literatures arise from differences in the ability of these two data sources to capture top incomes or from the application of different income constructs based on these data sources. In this paper, we do just that.

Using internal CPS data, we examine income inequality trends since 1967 using the inequality measures and income distribution definitions developed by Piketty and Saez (2003) and others using tax return data. Doing so, we can largely match their results. Our estimates of top income share levels and trends are nearly identical for groups in the richest tenth with the exception of the richest 1 percent. Even for estimates of the share held by the top 1 percent, the two data sources are broadly in agreement about trends over much of the past 40 years. It is only during a six year period in the late 1990s that the trends diverge for reasons that are not easily explained by changes in the nature of the two data sources.

Data

Our analysis derives from access to internal CPS data which are identical to the data used by Census Bureau researchers in their official work (see e.g. U.S. Census Bureau, 2009). These data measure top incomes much better than the data released in public-use CPS files. To protect the confidentiality of its respondents, the Census Bureau censors ("top codes") each of the income sources received by individuals. This practice must be addressed in order to derive sensible estimates of top income shares using CPS data. The advantage of internal data over public-use data is that the prevalence of topcoding is very much lower.[2] For example, in 2004, 0.5 percent of individuals lived in a household in which some source of income was topcoded in the internal data compared to 4.6 percent in the public-use data.

Even the small extent of censoring in the internal CPS data produces biased estimates of top income shares. To address this issue, we use a multiple imputation approach in which values for censored observations in the internal data are multiply imputed using draws from a parametric model of the income distribution fitted to the internal data. The Generalized Beta of the Second Kind (GB2) model used here is widely used in the income distribution literature, and shown to fit income distributions extremely well across different periods and countries: see e.g. Bordley, McDonald and Mantrala (1996), Brachmann, Stich and Trede (1996), Bandourian, McDonald, and Turley (2003), Feng, Burkhauser, and Butler (2006), and Jenkins (2009). Since the GB2 is a four-parameter distribution, its shape is more flexible than that of the Pareto distribution which has also widely been used in the literature to describe the top of the income distribution.

The multiple imputation approach used here is the same as that used by Burkhauser et al. (forthcoming) and described in detail by Jenkins et al. (forthcoming). This approach first involves fitting a Generalized Beta of the Second Kind (GB2) distribution for each year's data by maximum likelihood, accounting for individual-level right-censoring.[3] We then randomly draw values from the income distribution that is implied by the fitted GB2 distribution and impute these to censored observations, estimate inequality indices using the distribution comprising imputations for censored observations and observed incomes for non-censored observations, and repeat the whole process one hundred times for each year. Estimates of inequality indices such as top income shares are derived by combining the estimates from each of the one hundred data sets for each year using the 'averaging' rules proposed by Rubin (1987), and modified by Reiter (2003), to account for imputation variability. This combination of Internal CPS data with multiply imputed values for censored incomes provides the best available CPS-based estimates of the income distribution. It is the source for all the CPS-based estimates of top income shares that we compare with the tax record-based estimates of top income shares of Piketty and Saez (2003).

We believe that the flexibility of the GB2 distribution allows for a better fit of top incomes than the Pareto distribution but acknowledge that both distributions are widely used to impute top incomes in the inequality literature. Fichtenbaum and Shahidi (1988), Bishop, Chiou, and Formby (1994), and Piketty and Saez (2003), for example, use the Pareto distribution. Thus, in Appendix A, we explore the implications of using a Pareto imputation instead. We compare the Pareto β coefficients describing the shape of the right-tail of the distribution that are implied by our CPS data with those that we calculate from the data appendix of Piketty and Saez (2007). In general, the β coefficients from our multiply-imputed distributions are slightly smaller than those derived from Piketty and Saez's data. This indicates that, if we had assumed that a Pareto distribution with the Piketty-Saez β coefficients described top incomes in the CPS data, the top 1 percent income share would be larger and even closer to their IRS-based results.

We have also undertaken all our calculations of top income shares using CPS internal data used "as is", without imputations for censored values. All the conclusions regarding income shares for income groups below the top 1 percent are unchanged. For the top 1 percent, using the unaltered internal data rather than multiply imputed internal data reduces estimates of income shares, but our conclusions about trends are similar. See Appendix A for further details.

Methods: Three Definitions of the Income Distribution

There are three substantial methodological differences between research based on the CPS and research based on the IRS tax return data. The first concerns the inequality measures used. Most CPS research employs either indices such as the Gini coefficient or Theil index that use data on all incomes, or indices like p90/p10 that ignore incomes at the very top of the income distribution. In contrast, tax data researchers focus on the top of the income distribution, defining inequality in terms of top income shares – the share of total income held by the richest 10 percent, the richest 5 percent, or the richest 1 percent, and so on – with larger income shares indicating greater inequality.

The other two differences in method concern the definitions of income, specifically: what is counted as "income" and what is the income-receiving unit. CPS-based researchers have typically defined income as pre-tax post-transfer income excluding capital gains: see e.g. Gottschalk and Danziger (2005) and Burkhauser et al. (forthcoming).[4] This includes all income collected on the March CPS questionnaire, which is intended to capture almost all cash income received by individuals. Two notable exceptions are realized capital gains and profit sharing income, including stock options, which are not captured in the CPS. (See Weinberg 2006 for a description of income sources collected and excluded in the March CPS data.) This income is aggregated to the household level, and deflated using an equivalence scale to account for differences in economies of scale and “needs” (the square root of household size is a commonly-used scale). Attributing the same size-adjusted household income to each individual within the same household, researchers examine the distribution of income among individuals.

Piketty and Saez (2003) and other researchers using tax data use different definitions. Piketty and Saez define income to include any income reported on IRS personal income tax returns before deductions and excluding capital gains. This encompasses “salaries and wages, small business and farm income, partnerships and fiduciary income, dividends, interest, rents, royalties, and other small income reported as income” (Piketty and Saez 2003, pp. 5–6). In addition to including stock options, which are not included in the CPS survey, a notable difference between this income definition and the CPS one is that the IRS definition excludes most transfer income, which is generally not taxable and not included in the adjusted gross income reported on tax returns. Hence it is close to the individual’s market income, which is also known as pre-tax pre-transfer income in the broader income inequality literature.[5] See Scholz and Levine (2002), Corneo and Fong (2008), and Bach, Corneo, and Steiner (2009) for examples of this type of measure.

Piketty and Saez (2003) aggregate income to the level of the tax unit rather than to the level of the household, do not adjust for differences in tax unit size, and examine the distribution among tax units rather than among individuals. An important issue in this literature is that not all individuals in the USA file a tax return, with non-filers generally having lower incomes. Therefore, estimates of the income share of the top 10 percent of tax filers understate the number of tax filers relative to the situation in which non-tax filers are included in the base. That is, when the number of "potential tax filing units" (filers plus non-filers) is the base, a higher share of actual tax filers and hence a larger share of reported pre-tax pre-transfer income must be included in order to correctly measure overall income inequality. To address this issue, Piketty and Saez (2003) estimate the total number of potential tax units and calculate the number of returns that make up the top income groups using this number. They define a potential tax unit as a married couple of any age, divorced or widowed individual of any age, or single individual over the age of 20. See the Data Appendix of Piketty and Saez (2007) for further details.

Definitions of income and the unit of analysis are important because variations in each can be expected to lead to different inequality estimates. For example, we expect the inclusion of transfer income in income (as is done by CPS researchers) to reduce measured inequality because transfer income is targeted at poorer families while the inclusion of stock options in the IRS data likely increases inequality.

Additionally, low income individuals who need to share costs and lower living expenses are more likely to live in larger households with individuals outside of their tax unit. Therefore, aggregating income to the household level rather than the tax unit, and adjusting for economies of scale using an equivalence scale, may yield an inequality estimate that is lower than for the distribution of pre-tax pre-transfer income among tax units.

The two types of CPS series that we use are defined as follows. First, our "traditional" CPS series, labeled "CPS-Post-HH", refers to the estimates based on the distribution of size-adjusted pre-tax post-cash transfer household income among individuals, excluding capital gains. Size adjustment uses the square root of household size.

The second CPS-based series, "CPS-Pre-TU", uses Piketty-Saez-type definitions of the income distribution. That is, we consider distributions of non-size-adjusted pre-tax pre-transfer tax unit income, excluding capital gains among tax units. Since tax unit identifiers are not provided in the CPS, we follow Piketty and Saez's procedures to determine potential tax units. All single individuals over the age of 20, married couples, and divorced or widowed individuals are considered to head a tax unit. Never-married children under the age of 20 are considered dependents and are assigned to the tax unit of their parent or guardian.[6] Our measure of pre-tax pre-transfer income includes income from wages and salaries, self-employment, farm income, interest, dividends, rents, trusts, and retirement pension income – which closely matches the taxable income sources included in the IRS tax return data analyzed by Piketty and Saez. Although a small number of taxable transfers are excluded by this definition, the broad income categories used by the CPS prior to 1987 make it difficult to separate these taxable transfers from non-taxable transfers consistently across the entire period. The vast majority of transfer income is non-taxable, and so our best approximation to Piketty and Saez's income definition necessarily excludes this income source.

Matching the procedures used for Piketty and Saez's primary income series, capital gains are excluded. This exclusion is both because capital gains are not recorded in the March CPS and because "[r]ealized capital gains are not an annual flow of income (in general, capital gains are realized by individuals in a lumpy way) and form a very volatile component of income with large aggregate variations from year to year depending on stock price variations." (Piketty and Saez 2003, p 6). However, as illustrated in the appendix of Piketty and Saez (2003), since capital gains are primarily received by high earners and this receipt has increased over time, including capital gains would likely raise the level of inequality and its increases in recent years. This would be true both using IRS-based data, where capital gains are included by some researchers, and using the CPS-based data, where capital gains are generally not included since they would have to be imputed as an addition to income recorded on the questionnaire.

Comparisons between the CPS-Post-HH and CPS-Pre-TU series are informative about how much of the difference in top share estimates can be attributed to differences in definitions, whereas comparisons between the CPS-Pre-TU series and the "Piketty-Saez" estimates reported by Piketty and Saez (2003, 2008) are informative about how much of the difference in estimates can be attributed to differences in the underlying data source.

In order to contrast the three series at several points in the income distribution, we examine income shares for three groups within the richest tenth of the distribution each year. We consider the fortunes of those with incomes between the 90th and 95th percentiles of the distribution (the "p90–p95 group"), those with incomes between the 95th and 99th percentiles of the distribution (the "p95–p99 group"), and those in top 1 percent.

Top Income Shares: IRS- and CPS-based Series Compared

P90-P95 and P95-P99 income shares: In Figures 1 and 2 we provide our estimates of top income shares for the first two of the top income series defined earlier. The income shares for the p90–p95 group are presented in Figure 1 and the shares for the p95–p99 group are presented in Figure 2. For both groups, the estimates of income shares according to the CPS-Post-HH series are smaller than the corresponding ones from the Piketty-Saez series. This is unsurprising given the two very different income definitions used. Because a much greater share of non-taxable government in-cash transfers –Aid to Families with Dependent Children (AFDC), Temporary Assistance for Needy Families (TANF), Social Security benefits, etc. – are held by the poorest 90 percent of the pre-tax post-transfer (CPS-Post-HH definition) distribution, we would expect the income share of the top 10 percent of the pre-tax post-transfer income distribution to be smaller than the income share for the top 10 percent of the Piketty-Saez gross income distribution in all years. This is the case.

But, once we control for differences in definitions, the differences in estimates of income share held by these high income groups based on CPS and IRS data are much smaller in both level and trend. This can be seen by comparing corresponding estimates in the CPS-Pre-TU and Piketty-Saez series. For the p90–p95 group (Figure 1), the CPS-Pre-TU series and Piketty-Saez share estimates are almost identical in the beginning of the period. The increase in the CPS-Pre-TU series p90–p95 group's income share over the 40 year period is somewhat greater than the Piketty-Saez estimates: a rise from 10.9 percent to 12.5 percent, compared to a rise from 11.0 percent to 11.9 percent. But, even with the slight trend differences, the income shares in each year are always close to each other. For the p95–p99 group (Figure 2), levels and trends using the CPS-Pre-TU and Piketty-Saez series are even closer, although the CPS-Pre-TU series again shows a slightly greater upward trend than the IRS data.

In addition to comparing the income share of the p90–p95 and p95–p99 groups, we also considered the sources from which individuals in these groups received their income. However, the GB2-based multiple imputation procedure must be performed on total household income and thus cannot distinguish source-level incomes for this analysis. While this limits the usefulness of a comparison for the top 1 percent of the distribution, since most individuals in the p90–p95 and p95–p99 groups do not have censored incomes we can use the unadjusted internal data to compare the sources of income for members of these groups.[7] As discussed in Appendix B, for the p90–p95 and p95–p99 income groups, the sources of income for members of these groups are also similar between the CPS Pre-TU series and the Piketty-Saez series. This further supports the assertion that up through the 99th percentile of the income distribution, the IRS and CPS based results are similar once controlling for the differences in income and sharing unit definitions.

Top 1% income shares: Thus far, we have restricted our attention to groups with incomes lying between the 90th and the 99th percentiles. The similarities between the income shares in the IRS and CPS data for individuals in this range should be of comfort to both IRS and CPS researchers. The similarities mean that, up to the very highest incomes, the two datasets are consistent once there is reconciliation of the definitional differences described above. But what about the income shares of the top 1 percent?

It is only within this group that we see larger differences in results across the datasets. Figure 3 shows that the income shares for the top 1% of the distribution using each of our three series. In contrast to the earlier findings for the other two income groups, when using the same pre-tax pre-transfer income definition, a more sizeable unexplained gap remains between the datasets. It is worth emphasizing, however, that while the remaining difference is greater than for the other two income groups analyzed, the differences in absolute terms between the CPS Pre-TU series and the IRS series are relatively small, at least in earlier years. Before 1986 the income share for the top 1 percent is between 1 and 2 percentage points greater for the Piketty-Saez estimates relative to the CPS-Pre-TU series, although this difference expands in later years.

Trends in income shares: Arguably, inequality trends over time are of greater interest to researchers than inequality levels. In both the CPS Pre-TU series and the Piketty-Saez series we find slower growth in the share of income held by the p90–p95 and p95–p99 groups starting in the early 1990s than was the case in the 1980s. Thus, both the CPS and IRS data sources suggest that whatever top income concentration occurred during the 1990s, it was largely confined to increases in the share of income held by the top 1 percent.

So, what precisely has been happening to the top 1 percent's share? Prior to 1986, the trends in the income share for this group are remarkably similar according to all three series. Table 1 shows the average annual percent increases in the top 1 percent's income share for seven sub-periods. The two pre-1986 periods are the relatively low inequality growth period of the 1970s and the higher inequality growth period from 1980–1986. Each of the three series shows similarly small inequality growth in the 1970s, and the 1980–1986 period is even more similar as the Piketty-Saez series and two CPS series show almost identical average growth in the share held by the top 1 percent. It is only after 1986 that more substantial differences between the series begin to appear. The first of these differences occurs from 1986–1988, when the Piketty-Saez series shows a dramatic 22.1 percent annual increase in the top 1 percent income share. The increase according to the CPS-Pre-TU series is a more moderate 2.0 percent.

This divergence between series subsides in the period immediately after 1988. When the CPS-Pre-TU series is used, the difference in the top 1 percent's income share between this series and the Piketty-Saez one is just 0.2 percent per year from 1988 to 1992. Thus, when using similar income definitions, the trends in the income share of the top 1 percent are similar in both data sources for the entire period between 1967 and 1992 with the exception of 1986–1988.

From 1992–1993, the trends diverge again across series. In this year, both CPS series increase by over 40 percent while the IRS series falls by 4.9 percent. It is only from 1993–2000 that the IRS series shows a sustained increase in the share of income held by the top 1 percent relative to CPS-Pre-TU series. Over this period, the Piketty-Saez series estimates that the top 1 percent's share was rising at an accelerated pace. The 4.1 percent annual increase is more than twice the rate of increase in the early 1980s. By contrast, the CPS-Pre-TU series yields an annual increase of only 1.5 percent in the income share of the top 1 percent – which is a slower rate of increase than seen in the 1980s. But after the divergence for the 1990s, trends across series converged again from 2000–2006 and all three series show similar increases of between 1.3 and 1.5 percent average annual increases in the top 1 percent's income share.

So, for most periods during the past 40 years, the trends in top income shares are similar – once similar income definitions are used. There are no major differences in the trends implied by the different sources for the income shares of those with incomes between the 90th and 99th percentiles. It is only during the periods 1986–1988, 1992–1993, and 1993–2000, that the two sources show markedly different trends and only then for the top 1 percent of the population.

Explaining the differences in trends in the share of the top 1 percent

While the p90-p95 and p95-p99 series are quite close across the two datasets, what explains the divergences between series in estimates of the share of the top 1 percent for the periods 1986–1988, 1992–1993, and 1993–2000? We argue that the results for the first two periods arise from well-known limitations of the IRS tax return data and of the CPS, respectively.

For 1986–1988, we argue that the increased share of the top 1 percent shown by the Piketty-Saez series primarily reflects a change in tax policy rather than any genuine change in the incomes controlled by the richest 1 percent. The Tax Reform Act of 1986 provided substantial incentives for the very richest tax units to switch reported income from Subchapter-C corporations to Subchapter-S income and wage income. (See e.g. Feenberg and Poterba 1993, Slemrod 1996, Saez 2004, and Atkinson, Piketty, and Saez, forthcoming.) The tax law changes likely created a behavioral effect in how income is reported, which led to the very large observed increase in top income shares in IRS personal tax return data excluding capital gains over the course of these two years.

This blip therefore primarily reflects the IRS tax records improved ability to capture more of the income of this top income group after the 1986 Tax Reform Act. The high incomes observed after the reform were likely received by individuals at the top of the income distribution prior to the reform as well, but since personal income tax rates exceeded corporate tax rates individuals had a financial incentive to structure their income in ways that prevented it from appearing on personal income tax forms, or only appearing on personal income tax forms in the form of capital gains.[8]

In contrast, the CPS data shows no such increase between 1986 and 1988 after the Tax Reform Act. We suggest that this is because the CPS survey questions about income are broader than the detailed questions on IRS tax forms. As a result, nuances such as Subchapter-C versus Subchapter-S income that are important for taxpayers completing their tax return, and hence for the administrative records derived from them, do not have the same impact on CPS pre-tax income reporting. Since the CPS inquires simply about pre-tax income rather than making distinctions about whether the income is from a Subchapter-C or Subchapter-S corporation, the consequences of this type of reporting are of less personal consequence. Therefore, March CPS data are less sensitive than tax record data are to changes in the way in which people distinguish between different types of income in response to changes in tax laws.

Similarly, the divergence between the series for 1992–1993 reflects fundamental changes in the design of the CPS rather than a real change in income inequality. Over these years, the Census Bureau implemented a major redesign of the survey instrument, including a change to computerized rather than paper-based data collection methods. (See Ryscavage 1995 and Jones and Weinberg 2000 for details.) These changes, which also included allowing respondents to enter higher income values than allowed previously, improved the ability of the CPS to record all incomes but especially top incomes. We argue that this change in measurement primarily explains the increase of more than 40 percent in the top 1 percent's share in the CPS data during these years.

In both the case of the 1986-1988 increase in the IRS tax records and the 1992-1993 increase in the CPS data, the income shares after the blip should more accurately represent actual income at the top of the distribution. With the CPS data this is because the survey was redesigned with the intention of improving its capability to capture top incomes and with the IRS data this is because top earners are now reporting more of their income in ways that are captured on personal income tax records.

Since the 1992–1993 increase in top income shares in the CPS data primarily reflects a change in survey design and the 1986–88 increase in top income shares in the IRS tax records data primarily reflects a change in the way that tax units report their income, we explore the consequences of controlling for these artifacts of measurement. Figure 4 illustrates the level of top 1% income shares in each series over the past 40 years, upwardly adjusting the top income shares prior to the blips as if the better information on top incomes now observed were available prior to 1986 in the IRS data and prior to 1992 in the CPS data.[9] When this is done, the levels of the top 1 percent's share remain within 2.2 percentage points of each other across the two datasets until 1994 and the trends are quite similar other than the previously mentioned divergence from 1993–2000.

What explains the divergences for 1993–2000? Several factors could distort top income share trends in both series. For example, including capital gains would likely increase top income shares in both series. Conversely, including non-cash benefits (e.g. health insurance, food stamps, rent subsidies, etc.), housing stock appreciation, or measuring post-tax income would likely decrease top income shares in both series. However, since these factors are excluded from both datasets they will distort top income shares equally in both. Thus, the divergence must result from income sources that are excluded in one dataset but included in the other and which changed during the mid-1990s to influence the trends. Alternatively, the divergence could result from a shift in the ability of one or both datasets to capture top incomes over this period.

One potential explanation, as Reynolds (2006) suggests, is that changes in tax rules, requiring executive stock options to be reported as taxable income, led to the estimated rise in income share of the top 1 percent in the Piketty-Saez personal income tax series. According to this hypothesis, this group's income share has always been higher than observed (implying a greater difference between the Piketty-Saez and CPS-Pre-TU series). And importantly, trends according to the two series are more similar on the grounds that the more rapid increase in the Piketty-Saez series in the 1990s was an artifact of the changes in tax accounting rules. Alternatively, it is possible that the use of stock-options increased in the 1990s and that the IRS data accurately captured this increase but the CPS data did not since it does not ask about stock options. Thus, this hypothesis would suggest that the top income shares actually were increasing in the 1990s but the CPS data simply is unable to observe this change.

Another possible explanation is that a greater increase in the use of tax-deferred savings accounts (401k plans, Keogh plans and IRA tax shelters) by individual in top income groups outside the top 1 percent may explain part of the rise in the income share of the top 1 percent in the Piketty-Saez series for the late 1990s. Wolff (1998) finds that pension assets are much more important to individuals outside of the top 1 percent of the wealth distribution. However, Porterba, Venti, and Wise (2001) show that the ratio of all pensions including defined benefit and defined contributions to payroll was steady through at least 1999. Thus, if this explanation explains the discrepancy it is possible that it is because income previously received as defined benefits, which are missed by both the IRS and CPS data prior to retirement, is now received as defined contribution income, which is missed only by the IRS data. As a result, the CPS data could artificially observe slower inequality growth as individuals shift from unobserved to observed pension income. The IRS data, in contrast, would overstate the levels of top income shares by excluding this source of income primarily received lower in the distribution, but would be accurate in the trends.

Each of these explanations for the diverging trends is plausible but difficult to investigate further with either data set. The view that the CPS did an increasingly poorer job of capturing top incomes in the late 1990s is also plausible. But, if this is the explanation, the timing of the differences is curious. After its redesign in 1993, the CPS was better able to capture top incomes, as evidenced by the artificial jump in inequality in both of our CPS series between 1992 and 1993. Moreover, the prevalence of censoring during this period – after the internal data's topcodes were increased – was lower than it was in the mid-1980s or in the early 21st century.[10] So the CPS design changes should have increased the survey's ability to accurately observe top incomes during this period.

How might future research proceed to investigate these divergences further? Since the two datasets are remarkably similar below the 99th percentile and only diverge in the 1990s for the top 1 percent, researchers particularly concerned with this additional reconciliation of the datasets for the late 1990s should focus on elements of one or both datasets that effect trends differently during this period alone.

For researchers particularly interested in the top 1 percent income share in the late 1990s, the Survey of Consumer Finance (SCF) may be a fruitful source for comparisons. Wolff and Zacharias (2009) compare SCF estimates of top income shares to those of Piketty and Saez and find similar levels for the top 1 percent's share in recent years – although they observe more of the rise coming prior to 1994 than Piketty and Saez do. Kennickell (2009) compares SCF estimates to Piketty and Saez's estimates for income including capital gains and finds a top 1 percent income share in 2006 that is less than 1 percentage point below that reported by Piketty and Saez, along with similar, but slightly smaller, trends in the top 1 percent income share since 1994. Because the SCF produces top income share estimates that are in line with those from the CPS and IRS data, researchers interested in more fully understanding the 1993–2000 discrepancy between the datasets may be able to gain insight into the precise causes through a careful analysis that includes all three of these datasets.

Income inequality trends according to Gini coefficients

Thus far we have explored the ability of CPS data to capture trends in the share of pre-tax pre-transfer income going to top tax units in the IRS tax record data as measured by Piketty and Saez. But inequality trends can also be influenced by the choice of inequality index. It is less clear though, whether this choice has a practical impact on recent inequality trends in the United States. From country-level time series cross-section data, Leigh (2007) concludes that top income shares track other inequality measures reasonably well. However, to our knowledge, no previous study has performed a comparison of inequality trends using both the Gini coefficient and top income shares using a long run of comparable unit record data from the same country.

Since a top income share is the only inequality measure that can be readily derived from IRS tax record data we focus this analysis on the CPS data. Using the two CPS-based series, we compare the observed growth in income inequality using the Gini coefficient to the trend in the income share of the top 1 percent and the top 10 percent of the population. By using the same sample to compare results for these three inequality measures, we can determine the extent to which the choice of inequality measures influences the observed trends in income inequality.

Table 2 shows the average annual percent increases using these three income inequality measures in the CPS data for the seven subperiods since 1967 and for the entire 40 year period, suppressing the artificial increase from the 1992-1993 redesign.[11] Using either CPS-based income series, the two top income share series exhibit faster inequality growth than the Gini series when considering the entire 40 year period. When considering the subperiods, the pattern is mixed with the top 1 percent's income share exhibiting higher growth than the Gini coefficient in some periods (1980–1988, 1993–2000, and 2000-2006) and slower growth in others (1967-1980 and 1988–1992). During the period of greatest disagreement between the two literatures – from the early 1990s through the 2000s where the IRS-based literature has observed much larger increases in income inequality – this difference is quite large. Using the CPS Pre-TU series, the growth in inequality as measured by the top 1 percent's income share grew approximately 1.5 percent per year from 1993 through 2006. This compares to an average annual growth of just 0.3 percent per year in the Gini coefficient. (The growth in the top 10 percent's income share is much closer to that of the Gini.)

These results also help explain why researchers examining top income shares using IRS tax records have found continued inequality growth through the 1990s while researchers examining Gini coefficients using CPS data have not. We previously observed some differences in inequality trends between the two datasets during this period even using the same inequality measure. However, Table 2 shows that differences in the inequality trends observed in these two literatures also stem from differences in the inequality index used.

Since there are discrepancies in the top 1 percent income shares across the two datasets in the 1990s, however, this complicates the analysis for researchers who prefer the IRS based top 1 percent results but also wish to use the Gini coefficient to measure inequality. But since we have demonstrated that the IRS and CPS data are consistent up through the 99th percentile, it is possible to incorporate one's preferred top 1 percent series by using the Gini from the bottom 99 percent of the distribution from the CPS data along with information about the top 1 percent of the distribution from IRS data. This type of approach is demonstrated by Atkinson, Piketty, and Saez (2009). For researchers interested in combining the datasets in this way, Gini coefficients for the bottom 99 percent of the population estimated using our CPS-Pre-TU and CPS-Post-HH series are provided in Appendix Table C1.

Summary and Conclusions

We analyze trends in top income shares in the USA over four decades (1967–2006), with the goal of reconciling estimates derived from the CPS with those reported by Piketty and Saez (2003) and derived from IRS tax return data. Our CPS-based estimates draw on the internal data used by the Census Bureau to produce their official income statistics, which is a much better source for examining income distribution trends than CPS public-use data because the prevalence of topcoding is substantially smaller.

When applying a Piketty-Saez-type definition of the income distribution to CPS data (the CPS-Pre-TU series), we derive estimates of top income shares that are remarkably similar in terms of both levels and trends to those reported by Piketty and Saez (2003, 2008) for both the p90–p95 and p95–p99 groups. The shares grew in the 1980s and then slowed starting in the early 1990s. For the top 1 percent, our CPS-Pre-TU series provides a slightly lower share estimates than the Piketty-Saez series does but, with the exception of the period 1993–2000, the trends in the series are similar. Thus, we conclude that the differences in inequality trends observed by researchers using these two data sources are not primarily due to deficiencies in either data source but rather to the traditions of income inequality measurement used in the two literatures.

To explore this possibility further we also measure income inequality using Gini coefficient in the March CPS data, and compare results to those using top income shares. When using identical data, source of income, and income receiving units but different inequality measures, we found that the growth in the income share of the top 1 percent of the population substantially outpaced measured inequality using the Gini coefficient (Table 2). Thus, we conclude that at least part of the differing views in the two literatures about recent trends in income inequality can be attributed to differences in the literatures' measures of income inequality. Specifically, while the income divergence between the very top income holders and the rest of society was growing in the 1990s, the growth in income inequality across the entire distribution occurred at a more moderate pace.

When we use the same measure of income inequality – the income share of the top 1 percent – and similar income definitions – pre-transfer, tax-unit income – with the CPS data we are, for the most part, able to reproduce the same levels and trends Piketty and Saez find using the IRS tax record data. The only divergence in observed income inequality unexplained by a known deficiency in either or both datasets occurs over the period 1993–2000. It is possible that in this period of rapid economic growth, the CPS was unable to capture the rise in pre-tax pre-transfer income of the very richest people or that one or both datasets were limited in their analysis of income trends due to income that is outside the scope of their collection procedures. But, despite this limitation, users of both CPS and of IRS tax return data should be comforted by our finding that, for most groups at the top and for most of the past four decades, the differences in estimates from the two data sources are minor.

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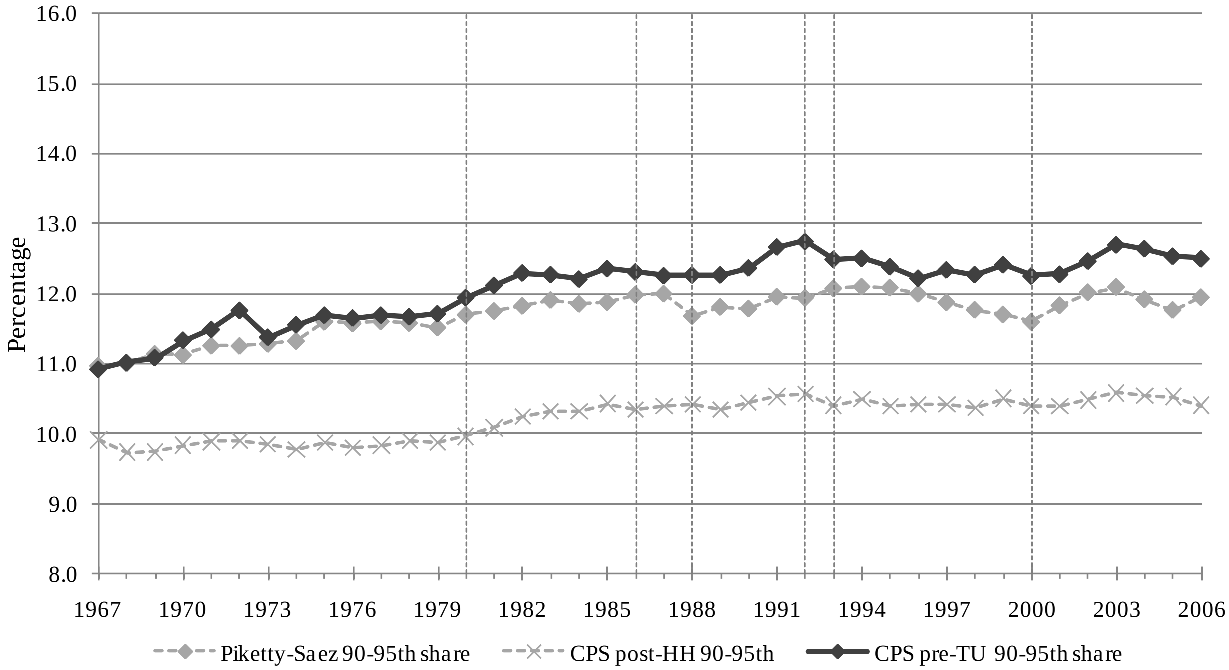
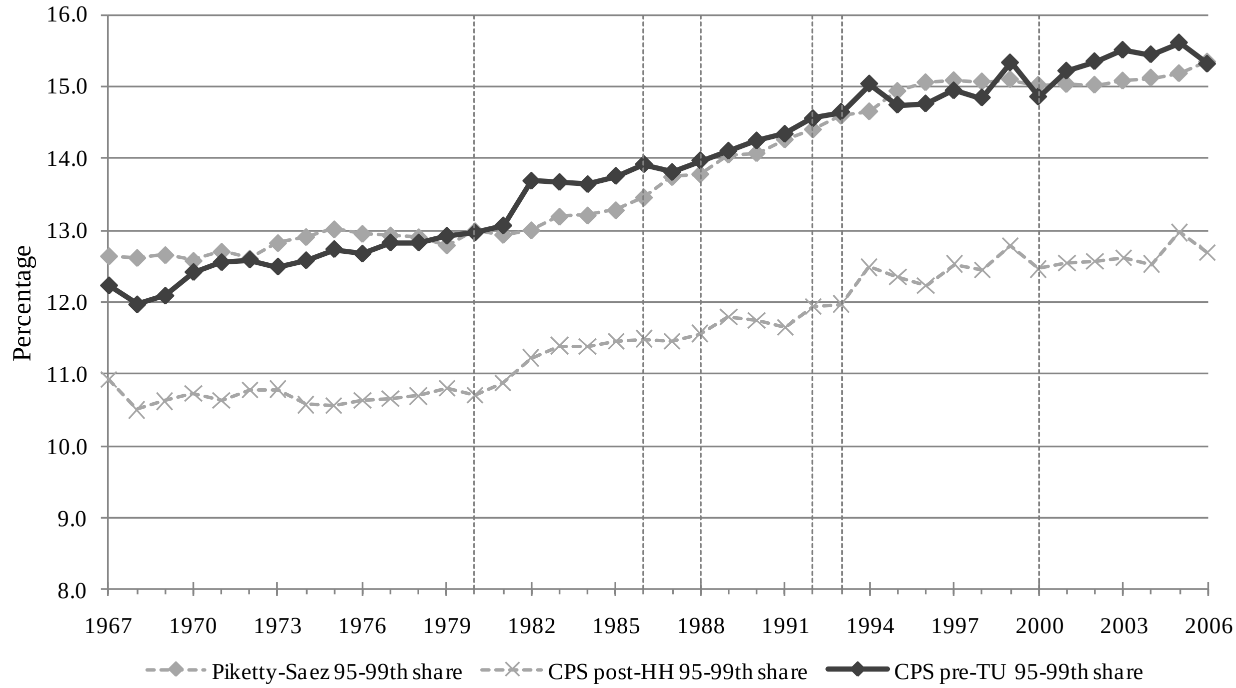
Figure 1: Estimates from CPS and IRS tax return data of the share of total income held by units with incomes between the 90^{th} and 95^{th} percentiles, 1967–2006



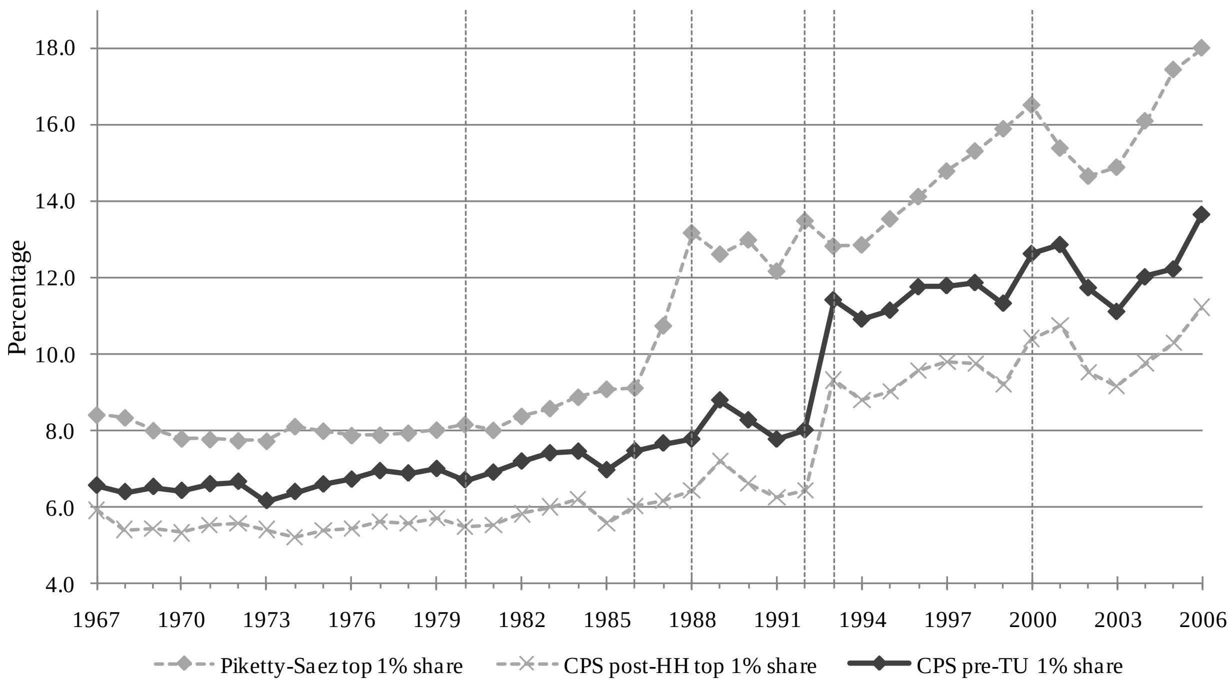
Sources. The Piketty-Saez series is taken from Piketty and Saez (2003, 2008). It refers to the distribution of pre-tax pre-transfer income among tax units. The CPS-based series were derived by the authors from CPS internal data. The CPS-Pre-TU series was derived using the Piketty-Saez definition; the CPS-Post-HH series refers to the distribution of size-adjusted pre-tax post-transfer household income among individuals. See main text for further details.
Note: Vertical lines delineate time periods displayed in Table 1 and discussed in the main text.

Figure 2: Estimates from CPS and IRS tax return data of the share of total income held by units with incomes between the 95th and 99th percentiles, 1967–2006



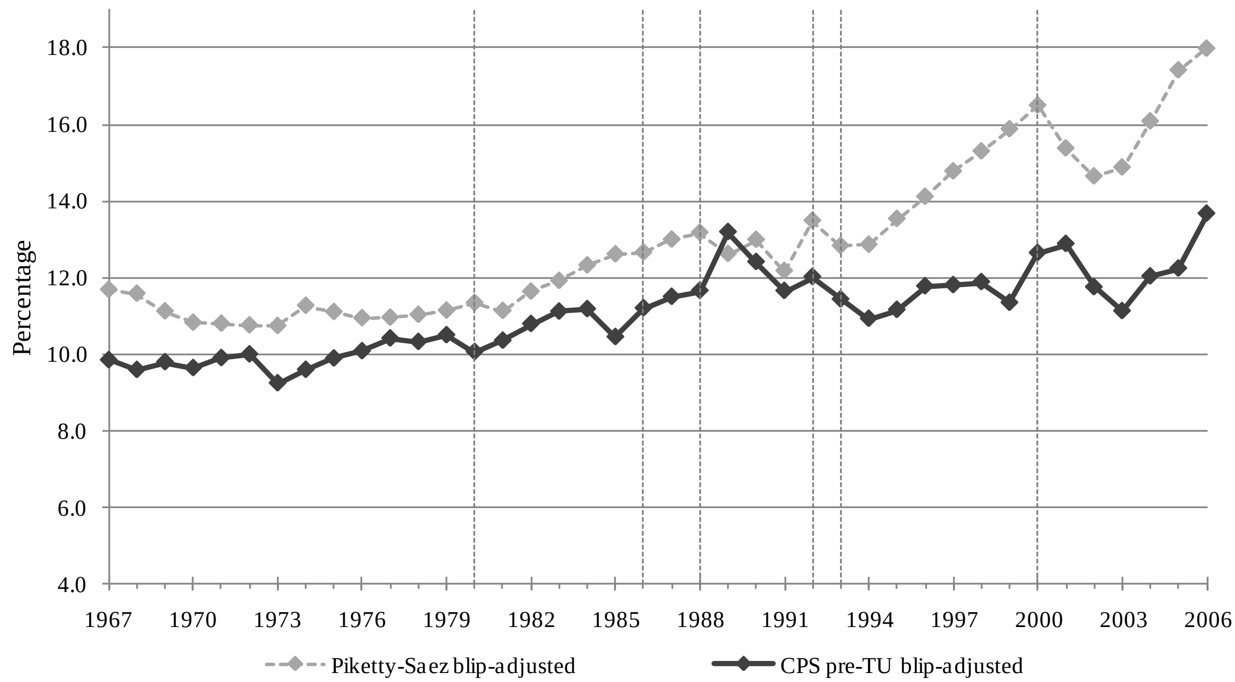
Sources and notes: see Figure 1.

Figure 3: Estimates from CPS and IRS tax return data of the share of total income held by the top 1 percent, 1967–2006



Sources and notes: see Figure 1.

Figure 4: Estimates from CPS and IRS tax return data of the share of total income held by the top 1 percent, 1967–2006, adjusting for measurement changes between 1986–1988 in the IRS data and between 1992–1993 in the CPS data.



Sources and notes: see Figure 1.
Note: The Piketty-Saez series is adjusted upward prior to 1988 to reflect the systematic undercounting of tax unit income captured in IRS personal income tax records prior to the 1986 Tax Reform Act. The CPS series is adjusted upward prior to 1993 to reflect the systematic undercounting of income from top-income households prior to the 1993 CPS redesign. To control for the difference between these measurement changes and actual changes in the blip years, it was assumed that the change in top 1% income shares from the unaffected dataset reflects the actual change in the top income share over the blip years.

Table 1: Average annual percentage change in income share of the top 1 percent, by subperiod between 1967 and 2006

Subperiod	March CPS		IRS tax return data
	Size-adjusted pre-tax post-transfer household income among individuals ("CPU-Post-HH")	Pre-tax pre-transfer tax unit income among tax units ("CPU-Pre-TU")	Pre-tax pre-transfer tax unit income among tax units ("Piketty-Saez")
1967–1980	–0.5	0.2	–0.2
1980–1986	1.7	1.9	1.9
1986–1988	3.2	2.0	22.1
1988–1992	0.0	0.8	0.6
1992–1993	45.0	42.5	–4.9
1993–2000	1.6	1.5	4.1
2000–2006	1.3	1.4	1.5

Sources: see Figure 1.

Table 2: Average annual percentage change in income inequality using three inequality measures, by subperiod between 1967 and 2006, adjusting for measurement changes in 1992–1993 in the CPS data.

Subperiod	CPS Post-HH			CPS Pre-TU		
	Gini	Share of Top 1%	Share of Top 10%	Gini	Share of Top 1%	Share of Top 10%
1967–1980	0.1	–0.5	–0.2	0.4	0.2	0.5
1980–1986	1.2	1.7	1.1	0.7	1.9	1.1
1986–1988	0.6	3.2	0.9	–0.1	2.0	0.5
1988–1992	0.4	0.0	0.5	0.9	0.8	1.0
1992–1993[a]	–2.0	–4.9	–2.0	–2.0	–4.9	–2.0
1993–2000	0.2	1.6	0.7	0.0	1.5	0.4
2000–2006	0.6	1.3	0.5	0.5	1.4	0.7
1967–2006[b]	0.4	0.6	0.4	0.4	1.0	0.6

Sources: see Figure 1.

[a] Following the procedure in Figure 4, the CPS series is adjusted upward prior to 1993 to reflect the systematic undercounting of income from top-income households prior to the 1993 CPS redesign. The change between 1992 and 1993 is reported as the corresponding change observed by Piketty and Saez (2003) using IRS records. Since the Gini coefficient cannot be calculated in the IRS data, the 1992–1993 change assumed for the Gini coefficient matches that in the IRS tax return data for the top 10% income share. From other years, this appears to be the closest approximation available in the IRS data.

[b] Following the procedure in Figure 4, the CPS series is adjusted upward prior to 1993 to reflect the systematic undercounting of income from top-income households prior to the 1993 CPS redesign, thus suppressing the 1992-1993 blip and replacing it with the corresponding change observed by Piketty and Saez (2003) using IRS records.

Appendix A. Sensitivity analysis: Pareto-based imputation and no imputation (unadjusted internal CPS data)

Imputation of some kind is necessary when one wishes to calculate income inequality for the entire income distribution including topcoded observations, and imputation has therefore been commonly-used in both the CPS-based inequality literature and the IRS-based inequality literature. To account for censoring in the internal CPS data (albeit of limited extent), we used the multiple imputation (MI) approach described in the main text. To investigate the potential sensitivity of our results to this choice, we also considered the implications of, first, using imputations based on the assumption that top incomes follow the Pareto distribution and, second, using no imputation at all, i.e. using unadjusted internal CPS data. To investigate the Pareto approach, we computed the β coefficients implied by our GB2-based multiply-imputed data and compared these to the β coefficients from Piketty and Saez's (2008) results. For any threshold, y, the Pareto β coefficient can be calculated as $\beta = \bar{y}(y)/y$, where $\bar{y}(y)$ is the mean income above the income threshold y. If the Pareto distribution correctly describes the distribution above a particular threshold $y°$, then estimates of β should be the same if re-computed using any threshold $y > y°$. For Pareto-based imputation to be robust, we would hope to observe little variation in the estimates of β with different top income thresholds. However, the values of β derived from both Piketty and Saez's and our datasets depend on the threshold chosen, and so we report values calculated for three thresholds (p90, p95, and p99). We derive them from our multiply-imputed CPS data for each year using our CPS Pre-TU income definition and compare them with the β coefficients derived from Piketty and Saez's IRS tax record data using the same thresholds. The estimates are plotted in Appendix Figure A1.

Using each of the three thresholds, the β coefficients implied from our GB2 estimation are somewhat lower than those in the IRS data. Since a higher β coefficient indicates greater concentration in the upper tail of the distribution, had we assumed that top incomes fit a Pareto distribution characterized by the parameters implied by the IRS data, the top 1 percent income shares would be slightly greater than those shown in the main body of the paper, and would likely be even closer to those reported by Piketty and Saez (2003).

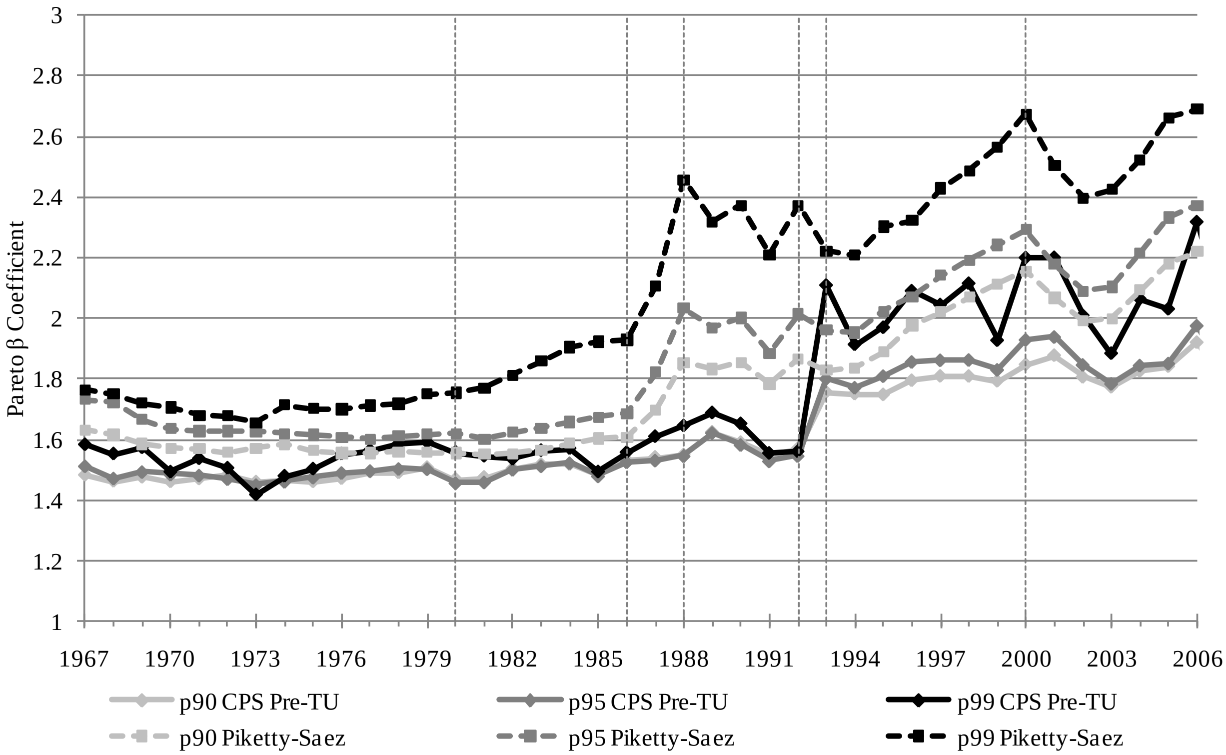
We also undertook all our calculations of top income shares from unadjusted internal CPS data used “as is”, i.e. without imputations for censored values. Appendix Figures A2 through A4 provide the top income shares using the pre-tax, pre-transfer tax-unit income definition estimated from both the unadjusted internal CPS data series and from our CPS data series which includes GB2-based multiple imputations for topcoded observations.

For the p90–p95 income group and the p95–p99 income group, the levels and trends in income shares derived from the unadjusted CPS data closely match those from the MI series, and both are close to the levels and trends shown by Piketty and Saez (2003) using IRS tax records. This is not unexpected as less than 1 percent of individuals lived in a household in which some source of income was censored in the internal data: censoring primarily impacts those in the very top income group.

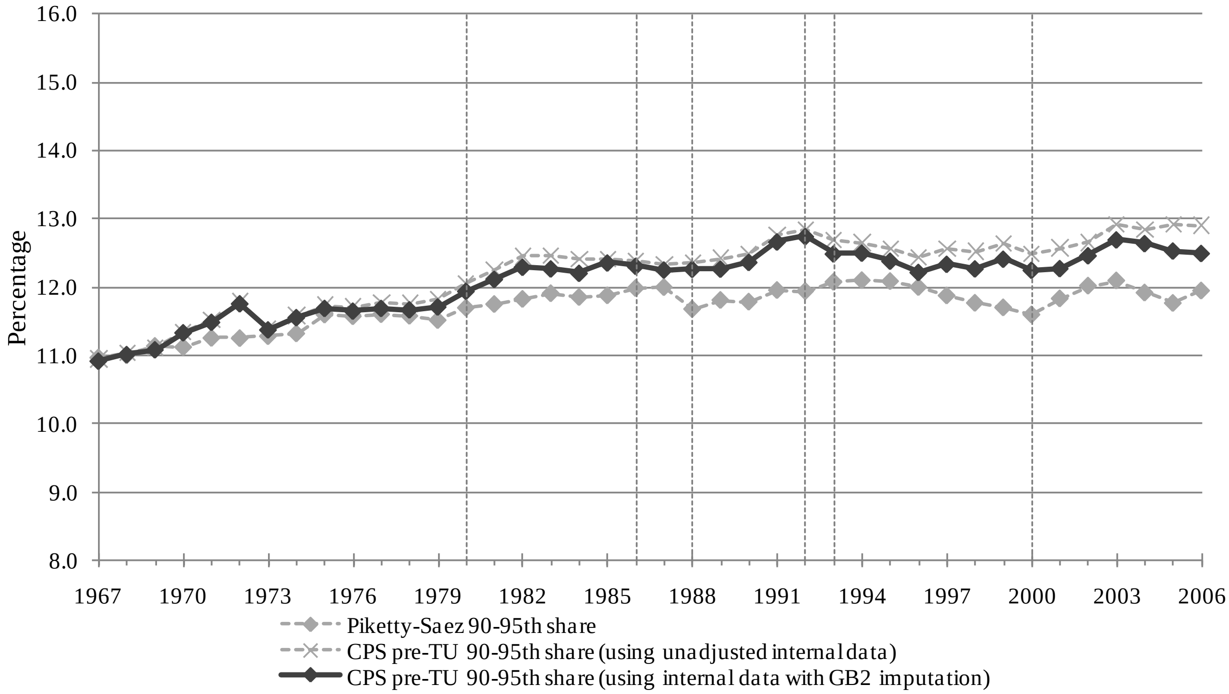
For the top 1 percent’s income share, using the unadjusted CPS data rather than the MI data results in a lower level of measured income inequality and a slightly lower income inequality growth. The general patterns of inequality increases are similar, however, with the top 1 percent’s share increasing at a pace similar to that shown by Piketty and Saez in the 1980s (although the unadjusted internal data observes the increase later in the 1980s than the other two series). As with the MI series, the rate of increase in the top 1 percent’s share then slows in the 1990s compared to that reported by Piketty and Saez before showing similar patterns again in the early 21st century.

Thus, our main findings hold even if no imputations are made for the small number of observations censored in the internal CPS data. Controlling for differences in income definitions and inequality measures, estimates using CPS and IRS data are consistent for almost all of the past 40 years with the exception of the mid- to late-1990s.

Appendix Figure A1: Pareto β coefficients derived from GB2-based multiply-imputed CPS data and IRS tax data, by top income threshold, 1967–2006

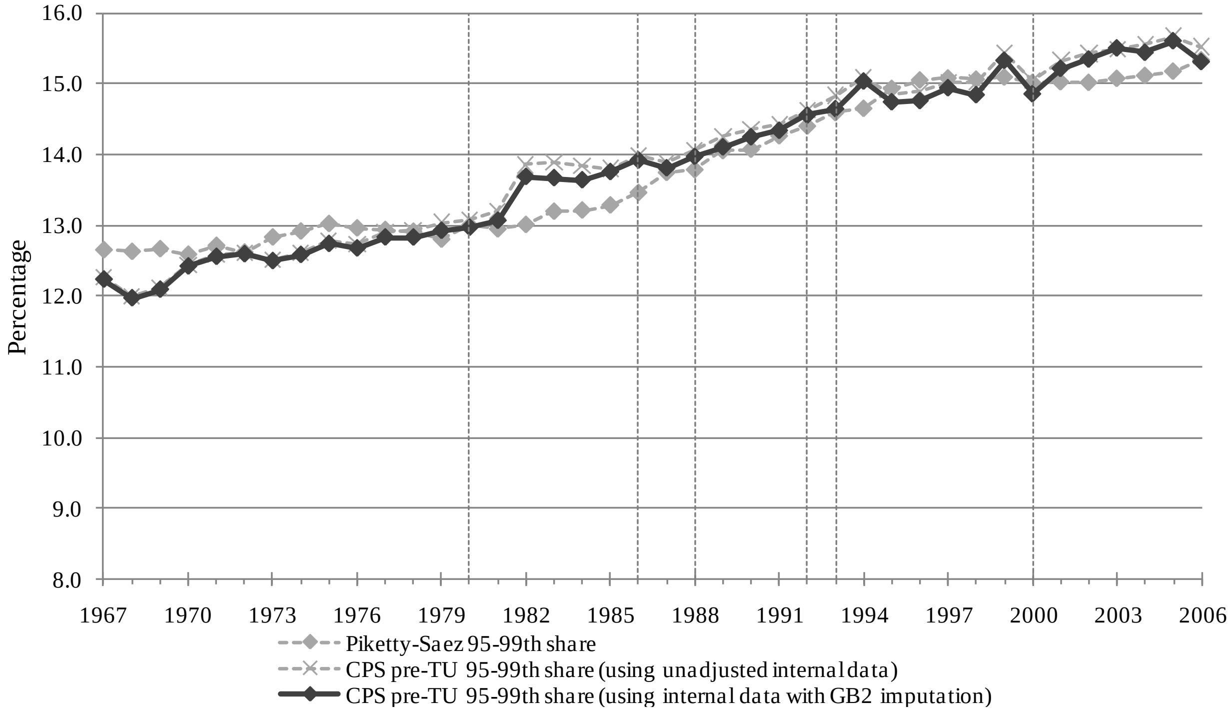


Appendix Figure A2: Internal CPS data estimates of the share of total income held by units with incomes between the 90th and 95th percentiles, with and without GB2-based multiply-imputed imputations for censored observations, 1967–2006



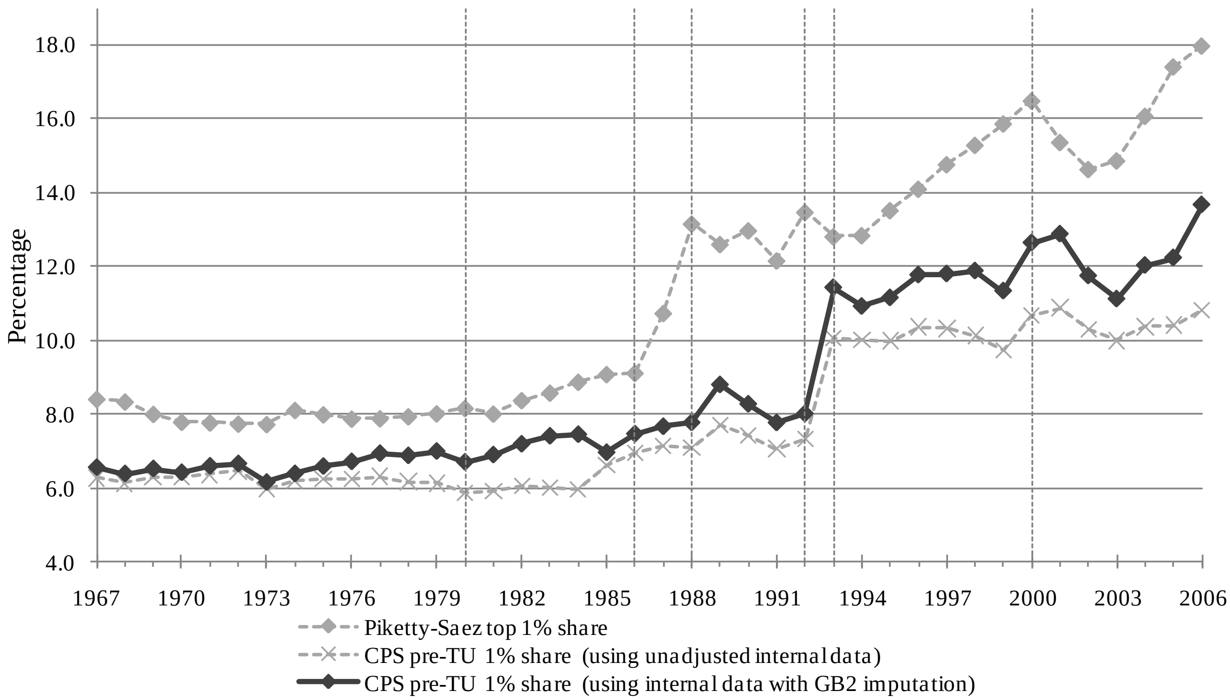
Sources. The Piketty-Saez series is taken from Piketty and Saez (2003, 2008). It refers to the distribution of pre-tax pre-transfer income among tax units. The CPS-based series were derived by the authors from CPS internal data. The CPS-Pre-TU series with the GB2 imputation matches the CPS-Pre-TU series from the main text, using our GB2 imputation to derive censored incomes in the internal data. The CPS-Pre-TU series using unadjusted internal data uses the unadjusted internal data “as is”. See Appendix A and the main text for further details.

Appendix Figure A3: Internal CPS data estimates of the share of total income held by units with incomes between the 95th and 99th percentiles, with and without GB2-based multiply-imputed imputations for censored observations, 1967–2006



Sources: see note to Appendix Figure A1.

Appendix Figure A4: Internal CPS data estimates of the share of total income held by the top 1 percent of units, with and without GB2-based multiply-imputed imputations for censored observations, 1967–2006



Sources: see note to Appendix Figure A1.

Appendix B. Sources of income: unadjusted internal CPS data versus Piketty-Saez data

Having established that, in general, the share of income in March CPS data going to the top 10 percent of the distribution closely matches that found in IRS tax record data by Piketty and Saez (2007), we also seek to understand how the sources of income compare for these individuals. When doing so, it is necessary to use the unadjusted internal data rather than the data based on our GB2-based multiple imputation (MI) procedure. This is because the MI procedure is used to impute the total income of right-censored observations and, hence, income sources cannot be identified for observations with imputed values. (It is infeasible to impute each income source separately and then aggregate across income sources. To do so, the imputation model would have to characterize cross-source correlations as well as the marginal distributions – the number of which would increase substantially in any case.)

By using the unadjusted internal CPS data rather than the MI data, we are unable to observe the actual incomes, or the sources of those incomes, for observations with censored income. But since many individuals in the top 1 percent of the income distribution have topcoded data, we are only able to provide meaningful income source information for the p90–p95 and p95–p99 income groups where censoring is less prevalent.

As illustrated in Appendix Table B1, the sources of income are similar for the p90–p95 income groups in the CPS and IRS data. The percent of income among members of this group received from wages ranges from 85.1 to 89.3 percent of income when using the CPS Pre-TU data, compared to a range of 86.9 to 91.6 percent of income when using the IRS tax records data. While there are some year-to-year fluctuations in the income received from wages, the level is remarkably stable in both the IRS and CPS data over the 40 year period.

Among the p95–p99 income group, the income shares are also as similar, with the share of income received from wages ranging from 74.8 to 85.7 percent of income in the CPS data and from 73.3 to 84.4 percent of income in the IRS tax records data (Appendix Table B2). There are only 5 years (1983, 1996, 1998, 1999) where the difference in the share of income received from wages is greater than 4 percent in the two datasets. Additionally, both datasets show increases in the portion of wages from income of approximately 7.5 percent over the 40 year period while the income from entrepreneurial activities declined. The only substantial difference between the series is that the IRS tax records data indicate that the portion of income from assets declined since 1967, whereas the CPS data suggest that asset income increased in importance to these high-income individuals. In general, however, not only do the IRS and CPS data closely match the share of income received by top earners in the income distribution, but they also provide similar results for the sources of that income.

Appendix Table B1: Income composition by source for tax-units with incomes between the 90th and 95th percentiles of the income distribution, 1967–2006

Year	CPS Pre-TU (Unadjusted)			Piketty-Saez		
	Wage	Entrepreneurial	Asset	Wage	Entrepreneurial	Asset
1967	86.3	10.3	3.3	88.2	7.3	4.6
1968	87.3	9.5	3.2	88.6	7.0	4.3
1969	88.8	7.7	3.4	88.6	6.8	4.6
1970	89.3	7.5	3.2	89.2	6.0	4.7
1971	88.1	8.8	3.2	90.1	5.6	4.3
1972	87.9	8.9	3.2	89.6	5.9	4.6
1973	87.3	9.1	3.6	88.8	6.4	4.9
1974	86.9	9.2	3.9	86.9	6.6	6.5
1975	87.5	8.6	3.9	88.7	5.6	5.7
1976	87.9	7.7	4.3	88.4	5.8	5.8
1977	88.2	7.7	4.1	88.7	5.4	5.9
1978	88.7	7.0	4.3	88.4	5.8	5.7
1979	87.8	7.6	4.6	89.1	5.2	5.7
1980	89.1	6.0	5.0	88.6	4.5	6.9
1981	87.3	6.6	6.1	88.1	3.7	8.2
1982	87.2	6.0	6.8	89.2	2.5	8.3
1983	85.1	7.5	7.3	89.5	3.4	7.1
1984	86.2	6.1	7.7	89.9	3.2	6.8
1985	86.9	5.8	7.4	89.9	3.2	6.8
1986	86.9	6.4	6.6	90.1	3.8	6.0
1987	86.5	8.0	5.4	90.1	4.3	5.6
1988	86.7	6.9	6.4	89.4	4.9	5.8
1989	85.7	7.8	6.5	88.6	4.9	6.5
1990	85.7	7.5	6.8	88.7	4.7	6.6
1991	86.3	7.8	5.9	89.4	4.7	5.9
1992	87.0	7.4	5.7	90.9	4.3	4.8
1993	88.2	6.3	5.6	90.9	5.0	4.2
1994	89.2	5.6	5.2	91.1	5.0	3.9
1995	88.4	5.6	6.0	91.6	4.5	3.9
1996	86.4	6.4	7.2	90.8	4.7	4.6
1997	85.7	6.2	8.2	91.0	4.8	4.2
1998	86.1	6.1	7.8	91.1	4.9	4.0
1999	85.4	6.4	8.2	90.6	5.5	3.9
2000	87.4	5.7	6.9	89.7	5.6	4.7
2001	87.8	5.8	6.5	91.2	5.0	3.8
2002	89.2	5.5	5.3	89.9	6.2	4.0
2003	88.5	5.4	6.0	90.1	6.3	3.6
2004	88.9	5.3	5.8	89.4	6.8	3.8
2005	88.5	5.0	6.5	88.1	7.5	4.4
2006	86.9	6.1	7.1	88.2	6.8	5.1

Sources: The Piketty-Saez series is calculated from Piketty and Saez (2007, 2008). The CPS-Pre-TU series using unadjusted internal data uses the unadjusted internal data "as is". See Appendix A and the main text for further details.

Entrepreneurial income includes self-employment and farm income. Asset income includes interest from interest, dividends, and rents. For comparability with the source-decomposition results presented in Piketty and Saez (2007), income from other sources are excluded and the sum of incomes from wages, entrepreneurial activities, and asset income is scaled to sum to 100 percent. Other forms of income represent less than 4 percent of income in all years.

Appendix Table B2: Income composition by source for tax-units with incomes between the 95th and 99th percentiles of the income distribution, 1967–2006

Year	CPS Pre-TU (Unadjusted)			Piketty-Saez		
	Wage	Entrepreneurial	Asset	Wage	Entrepreneurial	Asset
1967	74.8	18.8	6.4	73.3	17.4	9.3
1968	76.8	16.8	6.3	73.7	17.2	9.1
1969	77.9	15.3	6.8	75.3	16.1	8.6
1970	78.9	14.7	6.4	77.1	14.1	8.7
1971	79.1	14.6	6.3	77.6	13.4	9.0
1972	77.8	16.1	6.1	76.4	14.6	9.0
1973	75.9	17.3	6.8	74.2	16.0	9.8
1974	78.1	15.3	6.6	74.3	15.5	10.3
1975	78.9	14.7	6.4	77.4	13.3	9.3
1976	79.4	13.7	6.9	77.9	12.7	9.4
1977	79.0	13.9	7.0	78.1	12.4	9.5
1978	77.8	15.4	6.8	78.0	12.6	9.4
1979	78.3	13.1	8.6	78.4	11.5	10.1
1980	80.6	11.2	8.2	79.7	8.5	11.9
1981	79.2	11.0	9.8	80.6	6.1	13.2
1982	79.5	10.6	10.0	81.2	5.4	13.5
1983	78.9	10.8	10.3	83.4	5.7	10.9
1984	78.9	10.3	10.8	81.8	6.3	11.9
1985	81.2	8.7	10.1	82.9	6.6	10.5
1986	81.1	9.9	9.0	83.3	7.3	9.4
1987	80.1	10.5	9.4	81.8	8.9	9.3
1988	80.5	10.6	8.9	80.3	10.4	9.3
1989	78.1	11.3	10.6	79.3	10.3	10.3
1990	78.9	10.3	10.8	80.5	9.8	9.7
1991	79.1	11.0	9.9	80.8	10.2	9.0
1992	82.3	8.7	9.0	82.6	10.5	6.9
1993	80.8	10.3	9.0	83.2	10.7	6.1
1994	81.5	9.4	9.1	82.9	10.8	6.3
1995	82.8	7.2	10.0	82.9	10.8	6.3
1996	81.9	7.8	10.3	82.4	11.1	6.5
1997	78.1	8.7	13.2	82.0	11.0	7.1
1998	78.7	8.2	13.1	82.2	11.4	6.5
1999	76.8	10.5	12.7	82.2	11.3	6.5
2000	81.5	8.9	9.7	82.3	11.0	6.7
2001	83.5	7.5	9.0	83.2	10.9	5.9
2002	85.7	7.6	6.7	84.1	10.6	5.3
2003	84.1	7.8	8.2	84.4	10.6	5.0
2004	83.5	7.7	8.8	83.2	11.5	5.3
2005	83.5	7.3	9.3	81.5	12.6	5.9
2006	82.3	7.4	10.3	80.9	12.2	6.9

Sources: See note to Appendix Table B1.

Appendix Table B3: Income composition by source for tax-units with incomes in the top 1 percent of the income distribution, 1967–2006

Year	CPS Pre-TU (Unadjusted)			Piketty-Saez		
	Wage	Entrepreneurial	Asset	Wage	Entrepreneurial	Asset
1967	55.3	32.6	12.1	41.8	33.1	25.2
1968	52.4	33.5	14.1	42.0	31.5	26.5
1969	49.4	34.1	16.5	43.9	31.1	25.0
1970	56.0	29.6	14.4	45.6	30.0	24.3
1971	52.6	33.6	13.8	47.6	28.8	23.7
1972	55.7	30.9	13.4	49.3	27.2	23.5
1973	56.2	31.4	12.4	49.1	27.2	23.6
1974	54.4	30.3	15.4	49.4	26.2	24.5
1975	57.3	29.2	13.5	52.9	23.4	23.7
1976	57.8	28.2	14.0	54.7	22.0	23.3
1977	56.4	26.2	17.3	56.1	21.0	22.9
1978	59.4	27.5	13.2	58.1	19.6	22.3
1979	61.6	22.6	15.8	59.0	17.0	24.0
1980	63.8	17.9	18.3	60.5	13.3	26.2
1981	66.4	17.1	16.6	62.7	7.8	29.5
1982	65.1	16.9	18.0	62.6	8.2	29.2
1983	62.8	18.4	18.8	65.5	9.8	24.7
1984	59.9	15.8	24.3	66.1	9.9	24.0
1985	68.6	15.0	16.4	63.6	11.0	25.4
1986	68.1	15.1	16.8	65.7	11.1	23.1
1987	70.2	14.5	15.3	63.9	17.2	18.9
1988	69.5	16.2	14.3	59.8	21.2	19.1
1989	70.4	15.1	14.5	56.7	22.3	21.0
1990	68.2	15.8	16.0	57.9	22.3	19.8
1991	69.7	13.9	16.4	57.4	23.0	19.7
1992	73.0	15.2	11.7	61.6	23.6	14.8
1993	76.8	14.6	8.6	62.1	23.8	14.1
1994	81.6	10.9	7.5	59.1	26.8	14.1
1995	80.2	10.8	9.0	59.2	27.3	13.5
1996	80.7	11.0	8.3	59.7	27.0	13.3
1997	77.7	12.6	9.7	60.3	26.7	13.0
1998	77.3	14.2	8.5	61.1	26.6	12.3
1999	81.7	8.2	10.1	62.1	26.1	11.8
2000	82.0	10.6	7.3	63.0	24.7	12.3
2001	82.9	10.1	7.1	61.7	26.5	11.8
2002	86.9	8.3	4.8	61.2	27.4	11.4
2003	83.5	11.0	5.6	60.2	27.7	12.1
2004	84.7	9.0	6.2	58.4	28.4	13.2
2005	81.8	12.6	5.7	54.8	30.9	14.4
2006	82.0	10.8	7.2	53.5	30.1	16.4

Sources: See note to Appendix Table B1.
Note: Because censoring threshold changes vary by income source, the sources of income in the Unadjusted CPS data is particularly sensitive to changes in the topcode thresholds and, unlike results in the main text of the paper, these results are not adjusted using the GB2-based multiple imputation procedure. Thus, while income composition results are provided for the top 1 percent for completeness and as a reference for the reader, we discourage overanalyzing the composition of the top 1 percent due to these censoring concerns.

Appendix Table C1: Gini coefficients for the bottom 99 percent of the income distribution (excluding the top 1 percent) using the two CPS-based income definitions, 1967-2006

	CPS Post-HH	CPS Pre-TU
1967	0.339	0.457
1968	0.329	0.453
1969	0.330	0.458
1970	0.335	0.468
1971	0.337	0.476
1972	0.340	0.481
1973	0.338	0.463
1974	0.334	0.472
1975	0.338	0.482
1976	0.338	0.482
1977	0.341	0.484
1978	0.342	0.481
1979	0.345	0.481
1980	0.347	0.486
1981	0.354	0.493
1982	0.364	0.503
1983	0.370	0.503
1984	0.369	0.500
1985	0.369	0.502
1986	0.372	0.504
1987	0.372	0.501
1988	0.374	0.501
1989	0.376	0.503
1990	0.375	0.506
1991	0.376	0.513
1992	0.382	0.520
1993	0.392	0.530
1994	0.394	0.532
1995	0.389	0.526
1996	0.391	0.527
1997	0.394	0.527
1998	0.393	0.523
1999	0.395	0.526
2000	0.393	0.524
2001	0.396	0.532
2002	0.396	0.536
2003	0.400	0.540
2004	0.400	0.541
2005	0.404	0.541
2006	0.404	0.540

Sources: Authors’ calculations using Internal March CPS data

Endnotes

[1] See Atkinson, Rainwater, and Smeeding (1995), Atkinson and Brandolini (2001) and Gottschalk and Smeeding (1997) for reviews of the income distribution literature. For more recent examples of the use of the public-use CPS in measuring inequality trends in the USA, see Gottschalk and Danziger (2005), and Burkhauser, Feng and Jenkins (2009).

[2] For many indices of income inequality such as the Gini coefficient and members of the General Entropy class, researchers can replicate results derived from internal CPS data by using cell-means of topcoded incomes that are provided back to 1975 by Larrimore, et al. (2008). However, by construction, cell-means assume that all topcoded individuals have the same income. As a result, using cell-means to approximate top income shares with the public-use CPS data will lead to an overestimation of the income held by the 90th to 99th percentile groups and an underestimation of the income held by the top 1 percent of the distribution.

[3] To ensure that model fit is maximized at the top of the distribution, the GB2 is fitted using observations in the richest 70 percent of the distribution only, with appropriate corrections for left truncation in the ML procedure.

[4] In international comparisons of income inequality, it is most common to include the effect of both government transfer programs and tax policies by measuring post-tax, post-transfer income. See Atkinson and Brandolini (2001) and Gottschalk and Smeeding (1997) for reviews of this literature.

[5] In the wage inequality literature researchers tend to primarily be interested in how different types of workers – e.g. low vs. high skilled, women vs. men, etc. – are rewarded in the labor market. Hence in this literature it is common to measure pre-tax wage rates or labor earnings. Pre-tax pre-transfer market income is an extension of this concept to cover all factors of

production. Traditionally, researchers interested in income inequality have focused on how it relates to one's ability to consume and hence include government transfers in the US literature and both taxes and transfers in the international comparative literature. In those literatures, pre-tax pre-transfer income is rarely used by itself but rather to distinguish between incomes generated in the absence of government and a fuller measure of income which includes government taxes and transfers. In the CPS-based literature this has generally meant including cash transfers in income, thus using a pre-tax, post-transfer income definition for inequality estimation. Some researchers, including the National Research Council Panel on Poverty and Family Assistance, have advocated moving even farther from the pre-tax, pre-transfer market income definition when analyzing poverty by including taxes and non-cash transfers in US income inequality calculations. For a further discussion of the effect of such proposals on poverty rates and income inequality, see Burtless and Smeeding (2002).

[6] In the small number of cases where never-married individuals under age 20 live in a household without a parent or guardian, we assigned them to the tax-unit of the primary family in the household or the oldest adult in the household when there is no primary family. Only if there are no adults over the age of 20 in the household are they considered their own tax-unit. Different procedures for classifying these individuals were tested, including removing them from the sample, and assigning them their own tax units, which produced substantively similar results.

[7] While we provide the income source analysis for the top 1 percent in Appendix B, along with that for the lower income groups, we strongly caution against overanalyzing the results for this group because changes in censoring thresholds over time dramatically alter the makeup of income for this group which is not corrected for censoring using the GB2-based multiple imputation procedure.

[8] In the appendix of Piketty and Saez (2003), the series including capital gains illustrates a decline in the top 1 percent income share from 1986–1988 rather than the large increase shown for the top 1 percent income share when including capital gains. This suggests that the blip observed in the IRS data excluding capital gains in these years is partially attributable to income shifting to minimize tax liabilities. However, since capital gains income increased for top earners in the 1990s, when including capital gains there are greater increases in the top 1 percent income share in the IRS data in the 1990s (Piketty and Saez, 2003). These would likely exist in the CPS data as well if capital gains were captured there.

[9] In both cases, it is assumed that the change in top 1% income shares from the other unaffected dataset captures the actual change in top income share over the blip year. So, for 1986–1988, the change in the blip-adjusted IRS series is assumed to equal the 4.1 percent increase in the top 1 percent share seen in the CPS data and, for 1992–1993, the change in the blip-adjusted CPS series is assumed to equal the 4.9 percent decline in the top 1 percent share seen in the IRS data. The blip-adjustments also have a limited effect on the p90-p95 and p95-p99 income shares as the share assigned to the top 1 percent shifts. Figures illustrating the blip-adjusted income shares for these series are available upon request from the authors.

[10] See Larrimore et al. (2008) for detailed information about the prevalence of censoring in the internal CPS data year by year.

[11] For 1992–1993, since no Gini index is available in the IRS data when approximating the amount of the inequality increase that is real and the amount attributable to the redesign, it is assumed that the actual Gini increase matches the increase seen for the top 10% income share. This one-year assumption is only relevant for the average change over the entire 40 year period and the choice of this, or another reasonable assumption, should not greatly impact those results.