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Abstract

The Bureau of Economic Analysis and Bureau of Labor Statistics have estimated the first complete distribution of personal saving for the United States by estimating the joint distribution of disposable personal income and personal consumption expenditures. We start with household survey data augmented with data from administrative sources and modify these data such that they aggregate to the national accounts totals for 2004-2022. The augmented household survey data are corrected for suspected underreporting at the top and bottom of the income and expenditure distributions to allocate macro totals to households. While aggregate saving is 3% of personal income in 2022, we find it is negative for the bottom half of the distribution. In fact, expenditures are more than double income for the bottom 10%, but almost six times *less* than income for the top 1%. Despite a temporary increase in saving during the COVID pandemic, the polarization is large and persistent, and robust to modifying the definitions and sample composition. This paper represents an important step in bridging the gap between micro households and national accounts for saving.

JEL Codes: D31, E21, I31

Keywords: income distribution, inequality, consumption expenditures, saving

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1. Introduction

While income disparities dominate headlines, differences in consumption can also drive household perception of inequality. While the two are closely related for many households, differences in intergenerational wealth transfers and access to (and terms of) financing can lead to large gaps between income and consumption, leading to large differences in saving, whether positive or negative. Together, income and consumption are key determinants of well-being. By evaluating both for the same households, we can construct a distribution of saving and gain deeper insights into the multidimensional effects of tax and transfer policies. In principle, these household-level effects will then add up to economy-wide impacts.

Interest in producing distributional estimates consistent with macro (i.e., national accounts) totals has grown with the work of Stiglitz et al. (2009), as part of the international push to go beyond GDP in an emphasis on well-being.[1] A recent report by the National Academies of Sciences, Engineering, and Medicine (2024) provides guidance on developing an integrated system of income, consumption, and wealth to measure how economic prosperity is shared by households and evaluate effects of policy changes and economic shocks. This exercise is also consistent with recent System of National Accounts guidelines (and the work of research groups at the Organisation for Economic Co-operation and Development (OECD)) which advocate for globally consistent time series that reconcile macro totals and micro households.[2]

There is a huge volume of literature focused on the independent distributions of income, consumption, and wealth For reviews, see Johnson and Smeeding (2015), Atkinson and Bourguignon (2016), and Stone, et al. (2020). The work that is most relevant to our joint distribution exercise uses available data, rather than a structural model, to estimate relationships between those components. Two recent analyses have used information from multiple datasets to construct a joint distribution of income, consumption, and wealth for the U.S.: Fisher et al. (2022) and

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[1] Following the Stiglitz et al. (2009) report, the Expert Group on Disparities in National Accounts (EGDNA) and the Income-Consumption-Wealth group (EGICW) were founded over the next few years to promote the international research into constructing such measures. Research stemming from these groups has motivated a decade of work globally by encouraging researchers and statistical agencies to construct joint distributions and distribute national accounts totals to households.

[2] As interest in these topics developed, Ruiz (2011) created a foundational OECD framework which proposes a method to calculate nested Atkinson indices for the joint distribution of income, consumption, and wealth. Using this framework, Garner and Short (2013), construct multidimensional measures of economic well-being in the U.S. based on income, consumption, and wealth (using the Consumer Expenditure Survey) and find they offer more complete depictions than analysis along single dimensions alone. Specifically, examining only consumption (rather than the joint distribution) leads to an overestimation of well-being, since it is more equally distributed in the population. Additional studies on consumption inequality, such as decompositions by spending component and demographics, include Garner (1993) and Garner et al. (2003).

Balestra and Oehler (2023) (for which the U.S. results are based on calculations by Fisher et al.). This work has been done from a micro framework perspective and most closely follows the recommendations of the OECD (2013, 2023) reports. Although the two analyses have slightly different income, consumption, and wealth concepts, they share a core methodology based on the Survey of Consumer Finances (SCF), with some consumption elements imputed using the Consumer Expenditure Survey (CE).[3] The authors conclude that multi-dimensional inequality indeed increased faster than one-dimensional inequality owing to the overlap of households at the top. Prior to constructing the most recent joint distribution of income, consumption and wealth, Fisher et al. published a series of papers on this topic (2015, 2016, 2018, 2020) where they investigate the relationships between income inequality, consumption inequality, and wealth inequality independently and jointly. In terms of univariate distributions, they find that consumption inequality has not increased as fast as income inequality increased in recent decades in the U.S. (especially among the top 1%) given government transfers and smoothing behavior, but both tend to be higher among younger householders, those with less education, and non-White householders (Fisher et al. 2015, 2016, 2018).[4]

In contrast to the work based strictly on household microdata, the joint distribution results presented in the current paper scale household values to national accounts totals as published by the Bureau of Economic Analysis (BEA). We build on the past decade of research to estimate a distribution of personal saving (PS) in a national accounts framework, by estimating the joint distribution of income and consumption for 2004-2022, based on the BEA distribution of personal income (PI) and disposable PI (DPI) and the Bureau of Labor Statistics (BLS) distribution of personal consumption expenditure (PCE). The BEA PI distribution is based on the Annual Social and Economic Supplement of the Current Population Survey (hereafter, "CPS") and the BLS PCE distribution is based on the CE. We create a "comparable" income source between the two datasets and use multiple imputation to allocate most PCE categories (and other outlays) to CPS households.

[3] As in other distributional exercises (see below), here the term "consumption" is used as shorthand to mean "consumption expenditure". However, these two concepts are not quite equal. For instance, as measured in the national accounts and microdata, consumption expenditures do not include inter-household transfers of goods or services. While this distinction is unlikely to significantly impact the overall conclusions drawn from this analysis, it may have some distinct impact on estimates for those in the lower half of the distribution. Garner et al. (2023) compute a consumption measure which also includes flow-of-service values for vehicles and owner-occupied housing, as well as in-kind transfers. Also not included in consumption expenditures is home production; however, consumption would include the value of home-produced goods and services (see related Armstrong et al. 2022).

[4] A recent paper (building on several previous analyses) by Meyer and Sullivan (2023) finds that unlike income inequality (using the Current Population Survey), consumption inequality (using the CE) only increased in the top half of the distribution (1961-2017). Meyer argues that consumption better reflects economic well-being (better measured, more related other well-being measures).

To our knowledge, we produce the first complete distribution of saving, wherein all elements of DPI, PCE, and other personal outlays (PO) are distributed to households and scaled to national accounts (as opposed to distributing a subset or including non-DPI income concepts such as retirement income, capital gains, etc.) We find that though PS is only 3% of DPI, its distribution is highly polarized. PS is negative for the bottom half of the distribution (ranked on equivalized DPI), while highly positive at the top, ranging from -122% of DPI for the bottom decile to 83% of DPI for the top 1%. We confirm that overall income is distributed significantly less equally than consumption expenditures, even when scaling to national accounts totals, and that there is significant agreement in distributional ranking. That is about half of households are within the same decile (or next higher or lower decile) (e.g., decile 3 in consumption, but decile 2 or 4 if ranked by income), and 72% are in the same (or neighboring) quintile. Consumption is about twice as high as income for those in the bottom 10% of DPI, consistent with models which suggest significant debt (or drawing down of assets) for those with lower incomes.

We investigate the disagreement between income and consumption for the bottom half of the distribution and find this result robust to modifications to the definition of income, changes in sample composition, and omissions of the tail adjustments and scaling to macro totals. We further analyze certain households in “off-diagonals” (i.e., those with consumption significantly greater than income) and find that income is most likely significantly underreported for those groups. However, both the negative saving and proportion of households in the off-diagonal results are also consistent with those in Balestra and Oehler (2023).

There are a few key limitations to our analysis, which we explore in more detail in the discussion section. First, there is a considerable degree of uncertainty in any analysis which involves linking two different datasets on observables, but we believe we have taken steps to mitigate this measurement error. Second, we have adjusted both the income and consumption distributions to better reflect what we believe to be top values, but our results will be sensitive to our assumptions. Third, as we do not have panel data, we cannot observe the transitory nature of our measures over time, limiting our ability to draw conclusions about impacts on permanent income or mobility. Finally, while this paper does provide the first distributional saving estimate consistent with national accounts, we do not provide estimates of wealth, which would be ideal for a complete measure of household welfare.

This paper proceeds as follows. Section 2 discusses the data and methodology. Section 3 presents the results with a discussion Section 4. Section 5 presents the results.

2. Data and Methods

Prior to this exercise, BEA and BLS developed methodologies for estimating the distributions of PI (and subsequently DPI) and PCE respectively. With a prototype distribution of PI in March 2020, BEA re-established the regular publication of distributional estimates (Previously these had been published for some years in 1940-1970). Following the initial release and data user feedback, the suite of available results (time series and measures) has been significantly expanded and the methodology has been refined. The current methodology allocates 75 components of PI independently to CPS[5] respondents according to survey data and outside data sources including from the SCF, Statistics of Income, Medical Expenditure Panel Survey (MEPS), American Community Survey, and more (see Gindelsky 2023 for a detailed technical document). Once each component of PI is imputed to households such that the (weighted) imputations match aggregate totals from the National Income and Product Accounts (NIPA), it is equivalized by dividing by the square root of household size to compare households of different sizes to each other. Households are then ranked on equivalized PI (or DPI) for the published inequality series on the landing page, and in Table 2.10.

In 2022, BLS began researching methods to estimate the distribution of PCE using the CE surveys (Garner, et al. 2022) and published results for 2017-21 in December 2023 using updated methodology. The CE Interview survey is the basis for analysis, with some expenditures imputed from the Diary survey. The current methodology maps detailed CE data to roughly 150 PCE categories. In addition, several categories not collected by the CE survey are imputed from other datasets. For instance, the MEPS and administrative sources like the Center for Medicare and Medicaid Services are used to impute the in-kind value of health care. More details on the exact CE Interview sample selection, as well as a top-tail adjustment, are discussed in the next subsection. Following assembly of the data, imputations, and top-tail adjustment, expenditures are proportionally scaled so that weighted sample aggregates match NIPA totals by Major Type of Product (Table 2.3.5). For distributional statistics, consumer units are ranked by equivalized PCE using the square root of consumer unit size.

A. The CPS and CE

The first step in constructing a joint distribution of income and consumption is integrating the two datasets. We analyze data covering 2004-2022. The CPS contains many income variables for the distribution of PI (and

[5] We use CPS as shorthand for CPS Annual Social and Economic Supplements, the March survey whose purpose is to collect detailed income information.

subsequently DPI), while the CE contains many of the consumption items necessary for distributing PCE. Though the CE contains several income questions as well, its fundamental role is to serve as a detailed expenditure survey (unlike consumption and income survey data in other countries).[6] It is the richness of this consumption data which motivates researchers to impute consumption items using the CE, even if there is some consumption data in another survey.[7]

While it is a supplement to a labor force survey, there are several advantages to using the CPS for the income calculation. First, it is the survey presently used by BEA for the distribution of PI, with an established and well-researched methodology. This facilitates its use in the joint distribution. Next, the relevant household sample size of the CPS (56,839 in 2022) is significantly greater than that of the CE (roughly 5,000 each collection quarter, though for 2022 we used the subsample of 6,310 unique consumer units with at least two quarterly interviews and expenditures occurring between November 2021 and February 2023). Also, the CPS has more disaggregated sources of income, which are relevant for distributing some narrowly defined elements of PI to the right households. Its sample size allows for significant variation within the more detailed sources. Finally, the recall period is the previous calendar year. The survey is conducted when households are (theoretically) preparing their income tax returns to enhance recall of these target questions. Accordingly, official income in equality estimates of the Census Bureau derive from this survey.

For the joint distributional analysis, we generally sourced all income components from the CPS and all consumption components from the CE. However, we made two exceptions which are intended to harmonize overlapping DPI and PCE components in order to improve estimates of PS at the household level. First, instead of using the CE for all health-related expenditures, we used CPS values for the health items they have in common,

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[6] We also considered using the Panel Survey of Income Dynamics (PSID) as in the work of Fisher et al. 2016, Attanasaio and Pistaferri 2014, and Blundell et al. 2008. In addition to the advantage of increased consistency which comes from using the existing strategies of BEA and BLS based on the CPS & CE, the PSID has the disadvantage of more limited consumption information. Nevertheless, the trends found by the studies above found both convergence and divergence between income and consumption stemming from this survey. Blundell et al. 2008 also found "partial insurance" for permanent shocks, and almost complete insurance for transitory shocks, emphasizing the role of shock persistence on inequality trends.

[7] There are a few other notable joint analyses which use the CE. Aguiar and Bils (2015) find that though it appears that income inequality increased significantly faster than consumption inequality from an initial review of the data, there is much less divergence between the two measures than it appears when considering an Engel curve approach. The authors explain this by considering the shift in consumption away from necessities and towards more "luxury" goods by high income households. Krueger and Perri (2006) use the CE to investigate a pre-2000 relationship between consumption and inequality and also find that income inequality increased faster than consumption inequality, but that the difference during this period was driven specifically by divergence between the two measures *within-group* (i.e., within a race, education, or sex), rather than between the groups. They model this relationship and hypothesize that it is tied to risk-sharing within groups, and its relationship to borrowing.

including Medicare, Medicaid, and employer contributions. Second, instead of using the imputation method described in Gindelsky (2023), we distributed rental income of owner-occupied housing using CE rental equivalence values. These changes to the distributions of DPI and PCE have been used as inputs to calculate the joint distribution results including PS.

Unlike the SCF[8], the original CPS and CE do not oversample to ensure that the top tail of their respective distributions are represented. Therefore, they understate income and consumption in the aggregate (even accounting for definitional mismatch and scope, see Passero et al. (2014)) when compared to national accounts totals (Rothbaum 2015). It is possible that a significant portion of this gap is due to either (a) missing high income/consumption households, or (b) under response. Tax gap studies (DeBacker et al. 2020) show that much of the missing income is at the top (presumably the top 5%, see Fisher and Johnson (2022)). The BEA exercise employs a tail-adjustment strategy to capture this missing income by using information from the IRS's Statistics on Income dataset (see Gindelsky (2023) detailed description). However, there is no comparable administrative data available to suggest an appropriate distribution for consumption. To avoid underestimation of inequality, we follow the suggestion in Zwijnenburg, et. al (2022) and draw from a type-I Pareto distribution. This distribution is applied to the top 5% of total spending after adjustments and imputations, but before scaling to match the NIPA totals (comparable to the BEA technique of adjusting CPS responses prior to scaling to the NIPA totals). A shape parameter of 2 was chosen based on Zwijnenburg, et. al (2022) and our judgement on the relationship between income and consumption observed in the CE and SCF.[9]

B. Constructing a Comparable Measure of Income

Once PCE is allocated across all consumer units in the CE, we impute CU-level PCE to households in the CPS. We do this by linking the CE and CPS using multiple imputation and treating PCE at the CE level as "missing" for the households in the CPS. The first step in the process is to produce income deciles using a comparable income

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[8] "The Survey of Consumer Finances (SCF) overcomes both problems by oversampling at the top using administrative data derived from income tax records, and by verifying that the top is represented using targeted response rates in several high-end strata. The list sample ensures that the SCF has adequate representation of the upper tail of the wealth distribution and adequate representation of sparsely held assets." See more here.

[9] As part of a study of heterogeneous agent economies, Gaillard, et al. (2023) use the PSID to estimate Pareto parameters for different variables, finding a strict ranking of consumption, labor income, wealth, and capital income in order of thinnest to thickest tails. Though our definition of consumption differs slightly, and our choice of Pareto parameters differs from their empirical findings, we similarly find that income concentration is much higher than consumption concentration.

concept for both the CE and CPS. Although consumer units and households are not the same, for this exercise we treat them as sufficiently comparable.[10]

Linking the CE and CPS using income data that have not been adjusted to match national account definitions presents significant challenges. For instance, the recall periods are different for the CE and CPS; the CPS reference period is the calendar year while the reference period for CE collected income is the twelve months prior to the consumer unit's first or fourth interview. In part due to these differences, the income distributions tend to differ across the two surveys even for a narrow category like wages and salaries. Distributions of wages (and other important income sources) in the CE are shifted to the left relative to the CPS.

Our solution is to base our imputation procedure on a new income variable which we construct for this project. We call this constructed variable "comparable income," and its distribution lines up relatively well across the two surveys (see Figure 1). However, there are important income sources not included in comparable income which results in a slightly worse match at the tails of the distribution. Comparable income is 88% of DPI in aggregate (2017) and is distributed similarly (see Figure A1). Comparable income is formed by distributing selected NIPA amounts separately to observations in the CPS and CE using the methods from the BEA exercise (linked above). The measure includes some income sources (earnings, interest/dividends, and some transfers) which are collected in both surveys and which we have scaled to match NIPA totals included in PI and government accounts (see Appendix Table A1 for a full list). There are items (such as WIC) for which we must distribute NIPA totals with no corresponding CE information. For these items, we distribute the NIPA total to each CU with income sources that we presume are correlated, such as SNAP. For the 2013-2022 period, we also impute other unreported sources, such as tax credits, using TAXSIM.

C. Assigning CU-Level PCE to CPS ASEC Households: Multiple Imputation

Our comparable income measure is a key input into our imputation procedure. Specifically, we use multiple imputation with predictive mean matching, which uses PCE values from consumer units in the CE as imputed PCE values for similar households in the CPS.[11] Using actual values from the CE (rather than using model predictions) allows us to better preserve the distribution of PCE from the CE data and avoids specifying a particular distribution.

[10] In the CE, a consumer unit is defined as persons who share housing and make joint financial decisions, whether or not they are related (see BLS for complete definition). One residence can contain multiple CUs. About 97.5% of consumer units in our sample belong to households with a single consumer unit.

[11] We use Stata's "mi impute pmm" command (StataCorp, 2021) with five imputations.

Once comparable income is estimated for each unit of observation in the CE and CPS, they are ranked on equivalized comparable income, and assigned to deciles (in each respective survey). Using the CE, we then estimate separate models for each decile of equivalized comparable income and housing tenure group (owners and renters). For each income decile (see Figure 1) and housing tenure group, total PCE (at the CU level) is modeled as a function of demographic and income source indicators. The estimated models are used to predict values for all observations, and differences between predicted values form measures of distance between observations in the different surveys. For each CPS observation, a match is randomly chosen from the five "closest" CE observations in terms of the distance metric. Matches are only made within decile-tenure groupings.

The chosen CE observation's vector of PCE values is assigned to the CPS observation, with the exception of the overlapping health categories as previously discussed. As is done with the multiple imputation method, we compute statistics (e.g., the share of total PCE accounted for by the bottom 10% of equivalized PI) five times using the CPS (once for each of the multiple imputations of PCE). Computing results for each imputation better preserves the distribution of the original PCE estimates from the CE data. In our results, we report the averages of the five estimates for each statistic.

D. Computing Distributional Estimates

After the joint distribution of DPI and PCE has been constructed, we are able to compute a series of PS as in NIPA Table 2.1, line 34. We subtract PCE and other personal outlays (including interest payments and current transfer payments) from DPI to arrive at PS.[12] All distributional statistics are computed for an equivalized concept. This is done to ensure comparability of households of different sizes to each other. Which concept is used for ranking households is of great significance (i.e., comparing DPI and PCE when ranking on PCE or on DPI). This will be shown in the next section. We construct quantiles, including deciles and the top 1% and top 5% directly from the base CPS sample, with PCE and PS imputed to each household. As described above, the CPS is the much larger dataset and the most appropriate choice for these computations.

3. Results

[12] Personal interest payments are distributed according to interest payments as reported by respondents in CE. Personal current transfer payments are partially distributed using payment info in CE (including license/registration fees) where available. The remainder is allocated to be distributionally neutral.

We can first start by briefly reviewing the independent distributions of income and consumption (Table 1), in order to establish a baseline for examining the joint distribution and subsequently saving. Distributional results for PI and DPI are available on the BEA website for 2000-2022 (2022 is provisional) and BLS website for 2017-2021 (see Appendix Tables A2 and A3 for these series for 2004-2022). We then turn to the initial results from the joint distribution and finally examine the distribution of PS. For ease of presentation, we present our detailed cross sectional results for a single reference year of 2017, which is the current base year for the PCE deflator.[13]

A. Independent Distributions

An initial glance at the independent series (Table 1) shows that, as expected, DPI is significantly more unequal than PCE. While both average DPI and PCE have grown significantly over the period (PCE slightly more), the share of PCE accruing to the top quintile has fallen significantly, as compared to DPI, which has shown much less change. In both cases, the lower quintiles saw an increase in their shares of the aggregates. However, the two series have not always trended together. Though overall inequality fell from 2019-2021 for both DPI and PCE, it fell three times as much for DPI (Gini drop of 0.017 vs. 0.005). Real mean DPI grew more (7.3%) than real mean PCE (4.7%) over those three years, as did real median DPI (10.1% vs. 3.6% for PCE). These differences are largely attributable to the ways in which DPI and PCE were impacted by the pandemic. DPI rose significantly for households in the lower half of the distribution due to the significant expansions of unemployment insurance and the child tax credit, in addition to Economic Impact Payments. However, these changes did not necessarily result in proportional changes in spending.

There is significant variation underlying the aggregated income and consumption distributions. As shown in Table A2a, proprietor's income and income receipts on assets (interest and dividends) are distributed far more unequally than the other income items in terms of the shares received by each income decile, and of course, government social benefits are distributed the most equally (a significantly higher share at the bottom than other income items). Looking at the relative contributions of the components to income overall, it is clear that the overall distribution looks mostly like the distribution for compensation (63% of PI). The unequal distributions of interest and dividends and proprietor's income are mostly offset by the much more equal distribution of government social benefits.

[13] While results change quantitatively year-to-year, the results for 2017 are broadly representative of the overall period in terms of our main conclusions. The December 2023 BLS release of distributional estimates for PCE began in 2017 due to changes in the CE interview health insurance section which took place that year. See https://www.bls.gov/cex/ce-improvements.htm.

As seen in Table A3a, for PCE, the distributions of goods and services look roughly similar and like the overall distribution of PCE. However, durable goods are distributed significantly more unequally than nondurable goods (particularly food and gasoline). Among services, health care is most equally distributed. However, this may be a conservative allocation because it reflects a somewhat coarse distribution strategy which must impute and allocate the values of Medicare and Medicaid to households, in addition to employer premiums, using state averages from the National Health Expenditures survey (Garner et al. 2022). The distribution also includes out of pocket medical goods and services expenditures collected by the CE, which show significantly more variation. An unequal distribution can reflect true inequality in the expenditure or reflect (1) significant underreporting resulting in skew (as in the case of recreation goods and services) or (2) items that are out of scope for the survey, but still present in PCE (as in the case of financial services).

B. Joint Distribution

Turning to the joint distribution, it is useful to first start with the distribution of PCE, ranked on equivalized DPI (Table A4 gives the decile shares by PCE category; Table A5 ranks on equivalized PI instead of DPI).
Figure 2 shows the means and medians of DPI and PCE in levels ranked on equivalized DPI and the means of the top 1% and top 5% in the table below the chart. The corresponding chart/table ranked on PCE is in Appendix Figure A2, in addition to the ratio of PCE to DPI by decile. Immediately, we see that the ratio of mean PCE to DPI is quite high for the bottom 10% (2.14) vs. very low (0.17) for the top 1%. This highlights the principle that while consumption itself is unequally distributed, there is a pattern wherein households at the bottom likely consume more than their income (by means of debt or withdrawal from savings), proportionally, while those at the top consume less (keeping in mind the fact that income and consumption are defined in a national accounts framework here).[14] The pattern does not change if we use personal outlays (PO) as compared to PCE. Figure 3 shows the ln aggregate PO vs. DPI by equivalized DPI decile. The PO is significantly flatter than DPI, i.e. a significant change in income is not associated with as large of a large change in consumption.

Another way to look at the joint distribution is by examining the cross-shares in Table 2 at the quintile-level, similar to those presented in the OECD EGICW exercise (Balestra and Oehler (2023)) (see Table A6 for decile-level). In panel A, each cell in the table represents the share of households in each respective income-consumption quantile.

[14] Figure A3 shows the distribution of PCE (broken down into durables, nondurables, and services) vs. PI and DPI, with each series ranked on equivalized DPI (see Table A4 for detailed shares). Not only is the share of PCE much lower for the top quintile than their share of DPI (especially for nondurable goods), but the share of the bottom quintile is almost twice as high (10.4% for PCE vs. 6% for DPI). The shares of the middle two quintiles are more comparable.

We can see that only 4% of households are in the top decile of both income and consumption (11% in the top joint-quintile). About 1/5 of households are in the same income & consumption deciles, but about half are within (same or adjacent) a decile. Compared to the OECD results (Table A7), our results are a little less concentrated at the top. We can see the share of income in each bucket (Panel b) and share of consumption (Panel c) to further get a sense of the distribution. For example, 4% of the households are in the top joint decile and have 14% of DPI and PCE, whereas 4.4% of households are in the lowest joint decile and have about 1% of both income and consumption. However, the top 5% appears less concentrated in the joint distribution than the independent distributions: 1.5% of households are in the top 5% of both income and consumption and have 6.5% of income and 7.0% of consumption. Those in the top quintile of DPI in 2017 had 35.5% of PCE (compared to 48.0% of DPI) (Table 2 row sums).

As the analysis is conducted on a household level, we examine the race/ethnicity, age, and education of the household reference person.[15] Table 3 shows the demographic decomposition of each DPI quintile. Householders over age 65 are scattered throughout the distribution, though they are overrepresented in the middle quintiles, rather than the tails. Naturally, there is a higher share of reference persons enrolled in school at the bottom of the distribution, relative to the others. More Black and Hispanic householders are in the bottom of the distribution relative to their population share (and vice versa for the top quintile). Those in the bottom quintile are four times more likely to have a high school diploma only, whereas those at the top are two times more likely to have a college degree. The bottom quintile also has a much higher share of renters, three times that of the top quintile.

From Table 4, households with White, non-Hispanic reference persons are less represented in the bottom 10% of the joint distribution (relative to the independent distributions), while households with Black non-Hispanic reference persons who are under the age of 30 and those whose reference persons have less than a high school education. However, households in the top 10% of the joint distribution generally resemble those in the top 10% of each independent distribution much more closely (effectively an average). This suggests more concentration and less heterogeneity.

[15] The race/ethnicity groups are consistent with Census Bureau categorizations and are mutually exclusive, therefore here we will use "race" as shorthand for race and ethnicity. Although "Hispanic" is an ethnicity, rather than race, Hispanics represent a large and distinct ethnic group and are thus included separately in the breakdown, regardless of race. The omitted category includes those of mixed-race (non-Hispanic) and those who did not select one of the aforementioned groups for the primary response. While helpful for sample-size, the group is very heterogeneous and thus the results are difficult to interpret without a finer disaggregation.

C. Personal Saving

One of the fundamental advantages of constructing a joint distribution for households is to examine the distribution of PS. Figure 4a plots the distribution of PS by eq. DPI decile. Consistent with the data in Figure 3 comparing DPI and PO, most deciles have a negative share of PS. However, not all groups have negative average PS, though some households in each DPI quintile have negative savings (Table 3). Noting the differences in composition by quintile and demographic group in Table 3, we show average DPI, PO, and PS in Figure 5. Those aged 65 and older are the only group with average negative PS, likely due to excluded retirement income (see discussion below), while the highest PS is for those with at least a bachelor's degree. Interestingly, Black households have almost zero PS on average, while Asian households have the highest PS (2.4 times the average). While we cannot provide a causal explanation for this pattern, there are possibly differences in assets (and portfolio composition) and access to financing used to fund consumption by race (Gindelsky et al. 2023) (we return to this below).

These low (or negative) levels of PS that we presented for 2017 persist through the whole time series. Figure 4b plots real median PS by equivalized DPI quintile, illustrating the relative flatness within quintiles, with some business cycle variation. PS are negative for the bottom half of the distribution (bottom three quintiles, except 2020-2021 for the 40-60%). The primary volatility occurs during the pandemic when the ratio between income and consumption rises and then falls, as discussed above. This is consistent with the findings of Garner et al. (2024), who find that consumption fell disproportionately for households at the top. Generally, the trend of personal saving rises slightly throughout the period for top two quintiles while being flat for the others.

The negative saving at the bottom of the distribution warrants further discussion. There are two broad potential explanations for observing higher expenditures than incomes: (1) sources of income that are not included, and (2) financing of consumption via existing assets or debt.

First, there are sources of income that households have available for expenditure, but are not conceptually included in PI, such as retirement income and capital gains. Of particular relevance for lower income households is retirement income (though not Social Security, which is included). We expect the inclusion of (accurate) retirement income in this distribution would significantly increase income for households by 5-10%, especially at the bottom.[16]

[16] Since retirement income is underreported in survey data, this is likely an underestimate of the impact. Bee and Mitchell (2017) showed that administrative totals for retirement disbursements about double CPS survey estimates for 2012, before

There are also sources of inter-household transfers such as alimony, child support, parental support etc. which could lead to increased consumption, without a corresponding increase in PI.

Second, many households finance their consumption by taking on debt. Chiang and Dueholm (2024) found using the 2022 SCF that 51% of American households had credit card debt, with the highest proportion (60%) in the middle-income deciles. Households can finance large purchases, such as vehicles (80% of new vehicle purchases are financed[17]), with loans, rather than full cash outlays. However, the full value of the item is reflected in PCE. Additionally, households can take on debt to finance consumption more generally. While we cannot isolate an effect of debt on a specific purchase, we can consider some overall patterns. Credit card balances were approximately 6% of family income, according to the 2019 SCF, while debt service payments are 10% of DPI in aggregate. Moreover, while many households in the lower portions of the distribution do not have credit card debt (72%), Chiang and Dueholm (2024) found that the ratio of debt to monthly income for those in the bottom income decile with credit card debt was 90%. Some of those with lower incomes do not have credit cards but do take payday loans with very high interest rates, resulting in large debt servicing costs. While we cannot accurately measure debt for each household, it is likely that many households do have a significant share of consumption financed by debt.

D. The "Off-Diagonals"

Observing these overall patterns, one notices a substantial share of households are in the "off-diagonals" of Table 2a, i.e. with significant mismatches in income and consumption in terms of their ranking. Of particular interest are households in the lower quintiles of income with high consumption, as static budget constraints would not suggest such findings. Table 2a shows 4.4% of households are in Q1 for Eq. DPI and Q3, Q4, or Q5 for PCE. As discussed in the previous subsection, missing income and drawing on assets or debt are potential mechanisms of this mismatch. As a follow-up exercise, removing those (1) age 65+, (2) with retirement income, (3) currently enrolled in school, and (4) with negative income (driven by self-employment losses), we see a small decrease (down to 3.2%-3.4%) in the share of these off-diagonal households (see Table A8), but not a substantial one. This suggests that disagreement between the income and consumption measures go beyond simple demographic explanations.

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the recent redesign. Starting in 2018, the CPS has more nuanced retirement questions and values (Semega and Welniak 2015) which significantly increased incomes from retirement sources, but likely still underestimate administrative totals.

[17] This statistic comes from the National Automobile Dealers Association: Vehicle Financing | NADA.

While measurement error could be of concern when considering such disagreement, we find evidence against two potential sources: (1) the matching procedure, and (2) scaling to NIPA totals. As a sanity check, we check the joint distribution of income and consumption expenditures in the CE sample prior to imputing missing categories, tail adjustment, scaling to NIPAs, or any statistical matching. From Table A9, we note that there are also significant mismatches between income and consumption rankings when based on the CE survey alone. In fact, the percentage of consumer units who are in Q1 when ranked by after-tax income in 2017, but in Q3, Q4, or Q5 when ranked by expenditure, is 4.7%; this is very close to the same off-diagonal share in the CPS in terms of DPI and PCE (4.4%).[18]

Investigating further in Table A10, we can see that those in higher consumption quintiles, but low-income quintiles disproportionately have demographics of higher income groups. For example, those in Q1 for income of the CE but Q5 for consumption compared to those in Q1 for both are (1) over seven times more likely to have a bachelor's degree, (2) most likely to be White (80% vs. 49%), (3) three times more likely to own their homes (and have a much higher average home value), and (4) live in higher-income Census Tracts (by 60%). In expectation, they have four to five times the number of self-employed members. Analyzing their expenditure patterns, we see that there is no single category of expenditure which shows disproportionately high values for these off-diagonal groups. Rather, their expenditure is just higher across all categories. These observations lead us to believe that in addition to the possibility of drawing on assets or debt, it is likely that there is either significantly underreported income among income sources included in PI (see Hong et al. 2023 for an analysis of income underreporting in the CE compared to admin data), or else significant (non-retirement) income available to households to finance this consumption, likely to be better measured in the CE as it is designed to measure consumer expenditures.

4. Discussion and Conclusion

The primary advantages of constructing a joint distribution of income and consumption scaled to national accounts are (1) the ability to assess the impact of aggregate economic changes, whether they are structural, policy/tax, or business cycle related, simultaneously on income and consumption at a micro level, and (2) the construction of a distribution of saving. By scaling to national accounts totals, we can directly connect the micro distribution with the

[18] Using the CE survey alone, we also find considerable mass in the off diagonals when removing those who are either over 65, enrolled in school, or who have negative after-tax income. We also find similar shares when looking only at the subset which completed four interviews, for whom the income and expenditure reference periods differ by only one month.

macroeconomic trends, building on existing distributional work and contributing to the international efforts by creating a distribution that then sums up to national accounts totals.

We first confirm that the distribution of consumption is significantly more equal than income, when scaled to national accounts. The creation of these detailed distributional national accounts also allows us to examine the significant heterogeneity by income/consumptions source, with items such as durable goods and income receipts on assets distributed significantly more unequally than government social benefits or nondurable goods and services.

We next impute consumption and other outlays to CPS households, creating a joint distribution. The top quintile (when ranked on equivalized DPI) has 36% of PCE (compared to 48% of DPI), while the bottom quintile has 10% of PCE (compared to 6% of DPI). We find that there is considerable agreement between deciles of income and consumption (about half of households are within a decile), but a quarter of households are more than one quintile away. Moreover, examining the distribution during a period of economic turbulence (the COVID pandemic) does not change the fundamental relationships present in 2017.

Finally, we subtract outlays from income to create a distribution of saving. To our knowledge, this is the first complete distribution of PS—that is, distributing all components of DPI and PO to households, rather than a subset. In 2022, PS was only 3% of DPI (averaging 6% over the last 20 years), effectively meaning that in aggregate, income equals outlays for the household sector. As with other national accounts concepts, the aggregates do not show the significant distributional heterogeneity. We find that PS is negative for the bottom half of the distribution, about zero in the middle, and highly positive for the top, especially the top 1%.

We emphasize that this is a national accounts balance sheet, rather than a balance sheet as can be thought of on a household-level. Undoubtedly, a portion of the strong negative PS at the bottom of the distribution would be offset by the inclusion of retirement disbursements, inter-household transfers, and other sources of income not in PI. However, there may be similarly large transfers at the top of the distribution we are not observing, in addition to the (excluded) capital gains. The fact that there is likely missing income in both tails of the distribution suggests that the polarization of PS would be unlikely to be significantly altered if they were both included.

Moreover, we cannot discuss excluded income without noting that there are also a dozen sources of income which are imputed (such as imputed interest on pensions) and cannot be directly used by households for consumption.

PCE also contains some imputed or implicit components which are not “consumed” in the traditional sense (e.g., consumption of fixed capital for owner-occupied housing) and contains the full value of a purchase, regardless of financing (e.g., full car purchase price, though most households do not do a full cash outlay). Though definitionally appropriate, these imputed components will lead to a somewhat weaker relationship between PI and PCE than might be observed from examining a household balance sheet. However, we will continue to explore sources of possibly “missing” income contained in the definition of DPI in the next version of this analysis.

There are several limitations to our analysis. First, there is always going to be measurement error associated with any kind of imputation or statistical match, no matter how well-constructed or rigorously applied. We simply do not observe the joint distribution of DPI and PCE. Analysis of any matched dataset proceeds under the (fundamentally untestable) assumption that the key variables of interest (in our case, DPI and PCE) are statistically independent conditional on the comparable variables used in the linking procedure.[19] We explored several matching techniques and found our chosen procedure to be the best at preserving the marginal distribution of PCE as well as the joint distribution of PCE and comparable income. We judged the latter to be a high priority as income is an important determinant of spending. To the extent that there is leftover dependence between income and consumption after conditioning on our matching variables, our results could understate, for example, the inequality in PCE when ranked by equivalized DPI. While we have done our best to evaluate our statistical match, this remains a significant shortfall of any exercise involving a joint distribution estimated from two datasets which do not have the possibility of matching households exactly.[20]

Second, there is considerable uncertainty concerning inequality at the top of the consumption distribution. While we suspect that the CE underestimates consumption at the top, at present there is no clear way to directly correct for this. The results will be fairly sensitive to the shape parameter of the Pareto distribution chosen. For instance, a shape parameter of 1.7 increases the top 1%’s share of PCE by over 3 percentage points. Future research could seek to apply the methods of Zwijnenburg, et. al (2022) to fit another shape parameter to the distribution, or else make a different adjustment.

[19] For a discussion of conditional independence in statistical matching, see, e.g., Moriarty and Scheuren (2003).

[20] Rubin (1986) proposed (later refined by Moriarty and Scheuren, 2003) a parametric approach to dataset linking based on the multivariate normal distribution which builds in uncertainty about the conditional independence assumption. We are unaware of such techniques being used for income-expenditure dataset linking, but it is a potential avenue for future research.

We believe that this polarization of PS is quite robust and striking. Not only is it very consistent over the time period (with a definite bump during the COVID period before reverting to previous levels) [21], which indicates a limited role of matching error in any one given year, but it is corroborated by the Fisher et al. results in Balestra and Oehler (2023) which also report negative saving for the 2 bottom quintiles, despite including both capital gains and retirement income. Accordingly, this analysis represents an important (if incomplete) next step in measuring well-being by considering joint distributions in a national accounts framework. Although we have not yet been able to estimate the wealth dimension, there are several key results of the income-consumption relationship we believe to be salient. It is important to continue work in this area, improve the methodology, and extend the time series backwards to assess the trends.

[21] PCE and DPI do trend differently during the pandemic. Garner et al. (2024) examined consumption inequality during the COVID pandemic finding changes in consumption at the top of the distribution (i.e., reduced consumption of food away from home and entertainment). These changes can be juxtaposed against the gains in income from transfers for bottom quintiles, when considering the impact on the joint distribution.

Tables and Figures

Table 1: Comparing the Independent Distributions of Disposable Personal Income (DPI) and Personal Consumption Expenditure (PCE)

	2017		Δ2004-2022	
Inequality Metric	**DPI**	**PCE**	**DPI**	**PCE**
Mean ($2017)	$114,542	$102,371	+23.5%	+26.7%
Median ($2017)	$82,370	$82,838	+23.2%	+29.3%
0-20% Share	5.9%	8.5%	+0.2	+0.5
20-40% Share	10.6%	12.9%	+0.3	+0.6
40-60% Share	14.8%	16.4%	+0.1	+0.2
60-80% Share	21.0%	21.0%	-0.8	-0.4
80-100% Share	47.8%	41.1%	+0.2	-1.1
Gini Index	0.411	0.332	-0.017	-0.010
90/10 Ratio	4.9	3.64	-0.65	-0.31

Notes: These tables are reproduced from the BEA for DPI and updated from the BLS website from the December 2023 releases. For full methodology and details, please see the BEA and BLS landing pages. Real values are based on PCE price index.

Table 2: Joint Distribution: DPI and PCE Matrix (ranked on Eq. DPI) for 2017

		Equivalized Personal Consumption Expenditure Quantiles					
Equivalized Disposable Personal Income Quintiles		**0-20%**	**20-40%**	**40-60%**	**60-80%**	**80-100%**	**Total (Row)**
	(a) Share of Households						
	0-20%	11.1%	4.5%	2.3%	1.4%	0.7%	**20%**
	20-40%	5.3%	6.5%	4.5%	2.5%	1.3%	**20%**
	40-60%	2.2%	5.0%	5.8%	4.5%	2.4%	**20%**
	60-80%	1.1%	2.9%	5.1%	6.3%	4.6%	**20%**
	80-100%	0.4%	1.1%	2.4%	5.2%	10.9%	**20%**
	(b) Share of DPI						
	0-20%	3.2%	1.3%	0.7%	0.4%	0.2%	**5.8%**
	20-40%	3.1%	3.5%	2.3%	1.2%	0.5%	**10.5%**
	40-60%	1.9%	3.9%	4.3%	3.1%	1.7%	**14.8%**
	60-80%	1.3%	3.2%	5.4%	6.7%	4.6%	**21.1%**
	80-100%	0.9%	2.3%	5.2%	12.0%	27.5%	**47.8%**
	(c) Share of PCE						
	0-20%	4.1%	2.5%	1.5%	1.2%	1.0%	**10.3**
	20-40%	2.5%	4.0%	3.3%	2.4%	1.8%	**14.1**
	40-60%	1.2%	3.3%	4.8%	4.6%	4.0%	**17.9**
	60-80%	0.7%	2.1%	4.5%	7.0%	7.9%	**22.2**
	80-100%	0.1%	0.7%	2.1%	6.2%	26.2%	**35.5**

Notes: In panel (a), each cell represents the share of households in each PI & PCE quintile. In panel (b) each cell represents the share of PI for households in each PI & PCE quintile. In panel (c) each cell represents the share of PCE for households in each PI & PCE quantile. Each panel is constructed on a distribution ranked on equivalized DPI & PCE.

Table 3: Demographic of Reference Person by Eq. DPI Quintile (2017)

	Full Sample	0-20%	20-40%	40-60%	60-80%	80-100%
% Age 65+	**25.8%**	22.2%	32.7%	30.8%	23.9%	19.5%
% Age 25-64	**69.3%**	66.6%	62.0%	65.4%	73.6%	78.8%
% Actively in Labor Force	**63.4%**	47.1%	52.3%	60.7%	73.4%	83.6%
% Enrolled in School	**4.0%**	7.8%	3.4%	3.2%	3.2%	2.3%
% White	**66.4%**	53.0%	62.1%	67.2%	72.7%	76.9%
% Black	**12.7%**	20.8%	14.7%	11.6%	9.5%	6.7%
% Asian	**5.2%**	4.3%	4.1%	4.8%	5.3%	7.3%
% Hispanic	**13.6%**	19.0%	16.4%	14.3%	10.8%	7.4%
% Bachelor's Degree +	**35.1%**	16.7%	20.5%	31.6%	44.3%	62.6%
% HS Diploma only	**55.3%**	64.6%	65.8%	60.0%	51.2%	35.1%
% Renting	**35.6%**	60.8%	43.0%	31.8%	24.2%	18.5%
% PS <0	**54.0%**	83.1%	67.5%	55.9%	40.2%	23.0%

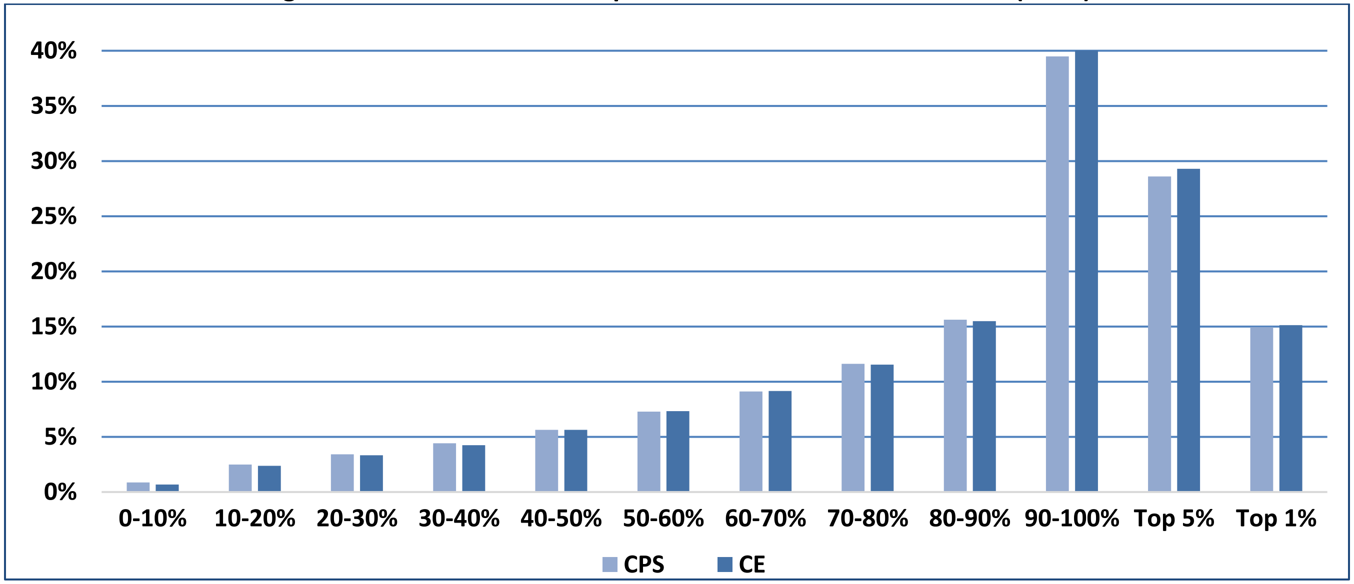
Notes: The first column ("full sample") shows the distribution by age, labor force status, race, education, and housing tenure. The last row is the percentage of the sample with negative personal saving. The following five columns show the distribution of those variables within each quintile, as ranked on equivalized disposable income.

Table 4: Demographic Disaggregation

	CPS	CE	PCE: Bottom 10%	DPI: Bottom 10%	DPI & PCE: Bottom 10%	PCE: Top 10%	DPI: Top 10%	DPI & PCE: Top 10%
Race								
White	66.4%	66.5%	43.7%	52.0%	44.2%	83.1%	78.8%	82.7%
Black	12.7%	13.1%	24.7%	22.9%	27.7%	5.7%	5.7%	4.9%
Asian	5.2%	4.8%	2.2%	4.8%	4.0%	6.2%	7.8%	7.3%
Hispanic	13.6%	13.7%	27.2%	17.2%	21.3%	4.0%	6.1%	3.7%
Other	2.2%	1.8%	2.1%	3.1%	2.9%	1.0%	1.7%	1.4%
Age								
<30	14.1%	14.6%	28.7%	26.6%	33.9%	3.6%	6.6%	3.1%
30-60	52.7%	53.1%	57.3%	47.5%	51.7%	47.4%	64.7%	58.9%
61+	33.2%	32.3%	14.0%	25.9%	14.4%	49.0%	28.7%	38.0%
Education								
Less than HS	9.5%	10.7%	25.6%	18.2%	20.9%	1.4%	1.6%	1.3%
High School	55.3%	54.0%	65.9%	64.4%	68.3%	28.4%	29.1%	23.9%
College +	35.1%	35.4%	8.5%	17.4%	10.8%	70.2%	69.4%	74.7%
Geography								
Non-Metroarea	14.2%	12.7%	17.6%	15.7%	15.9%	6.7%	8.6%	7.2%
Metroarea	85.8%	87.3%	82.4%	84.3%	84.1%	93.3%	91.4%	92.8%

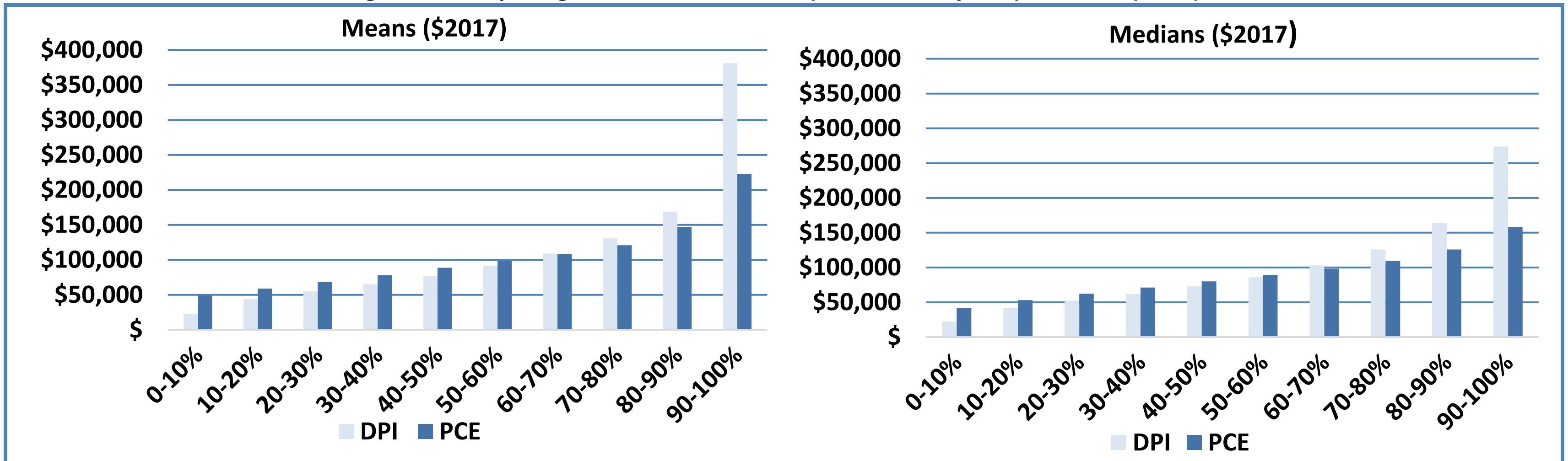
Notes: This table shows the percent of households in each race, age, education, and geographic group. Race, age and education refer to the reference person only. These racial groups are chosen to be consistent with Census Bureau categorizations and are mutually exclusive, therefore here we will use “race” as shorthand for race and ethnicity. Although “Hispanic” is an ethnicity, rather than race, Hispanics represent a large and distinct ethnic group and are thus included separately in the breakdown, regardless of race. The “other” category includes those of mixed-race (non-Hispanic) and those who did not select one of the aforementioned groups for the primary response. While helpful for sample-size, the group is very heterogeneous and thus the results are difficult to interpret without a finer disaggregation. Metroarea or non-metroarea is defined as in the CPS questionnaire. The first two columns represent the full CPS and CE surveys, while columns titled “PCE” are those which have been ranked by equivalized PCE (similarly with columns titled “DPI”). Columns titled “DPI and PCE” have been ranked on equivalized DPI and equivalized PCE, but represent those in the top or bottom quantile of the joint distribution.

Figure 1: Distribution of Comparable Income in the CPS vs. CE (2017)



Notes: The heights of the bars in this figure represent the share of "comparable income" held by each quantile as defined in section 3, when constructed (and equivalized) In the CPS and CE respectively.

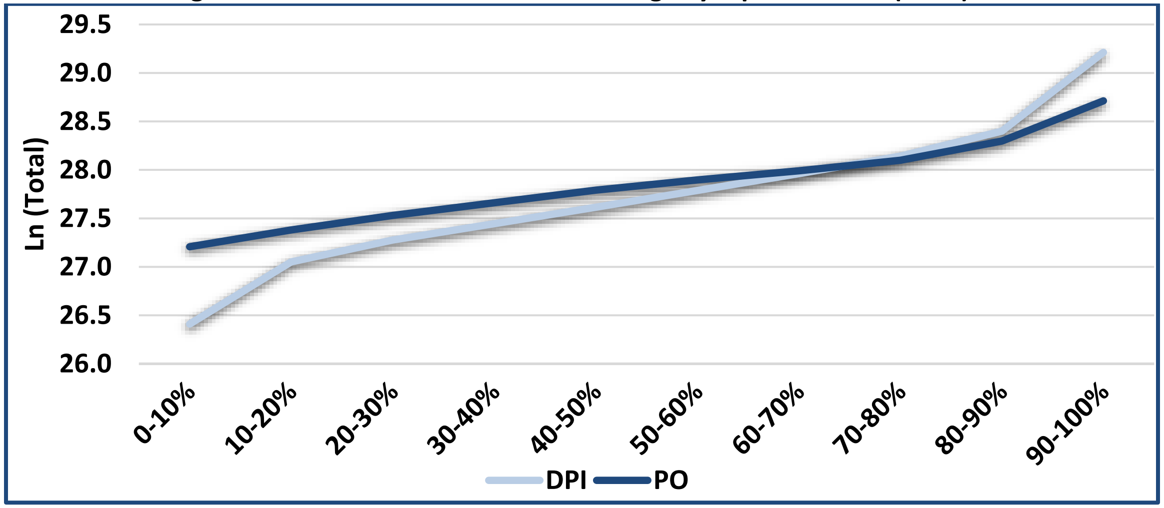
Figure 2: Comparing Means and Medians (ranked on Eq. DPI) in Levels (2017)



Income Rank	Mean DPI	Mean PCE
Top 5%	$531,989	$245,219
Top 1%	$1,302,517	$222,249

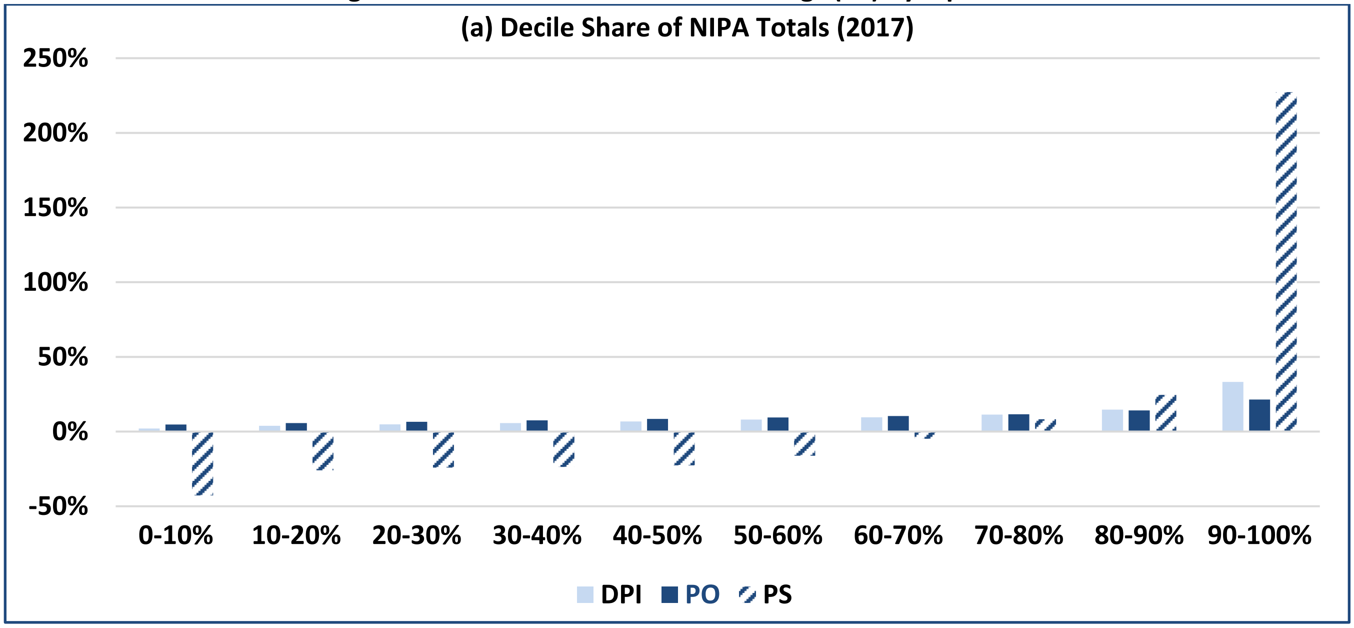
Notes: Figure 2a shows the quintile breakout within each income (or consumption category) when ranked on equivalized DPI. Figure 2b shows the means and medians of DPI and PCE for each quantile, determined by ranking on equivalized DPI.

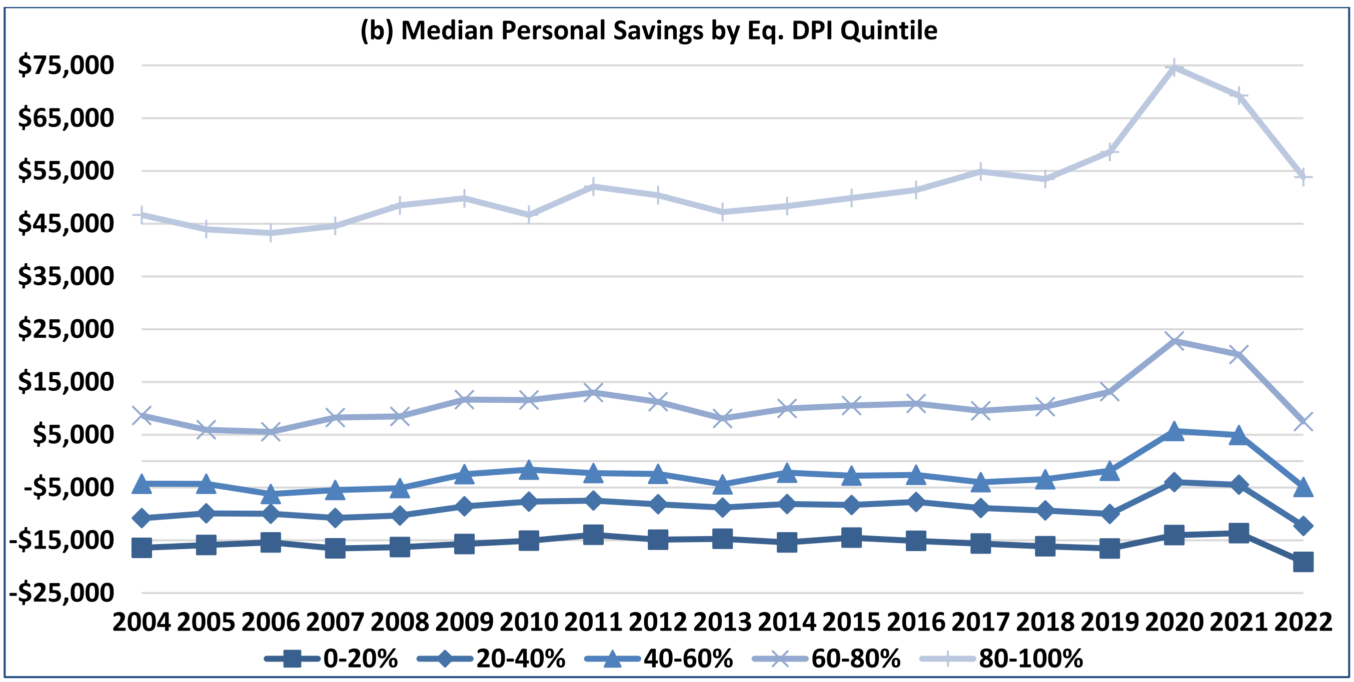
Figure 3: Total DPI and PO in Natural Logs by Eq. DPI Decile (2017)



Notes: Figure 3 shows the total ln(DPI) and ln(PO) for households ranked on equivalized DPI decile, i.e. the same set of households are in each decile.

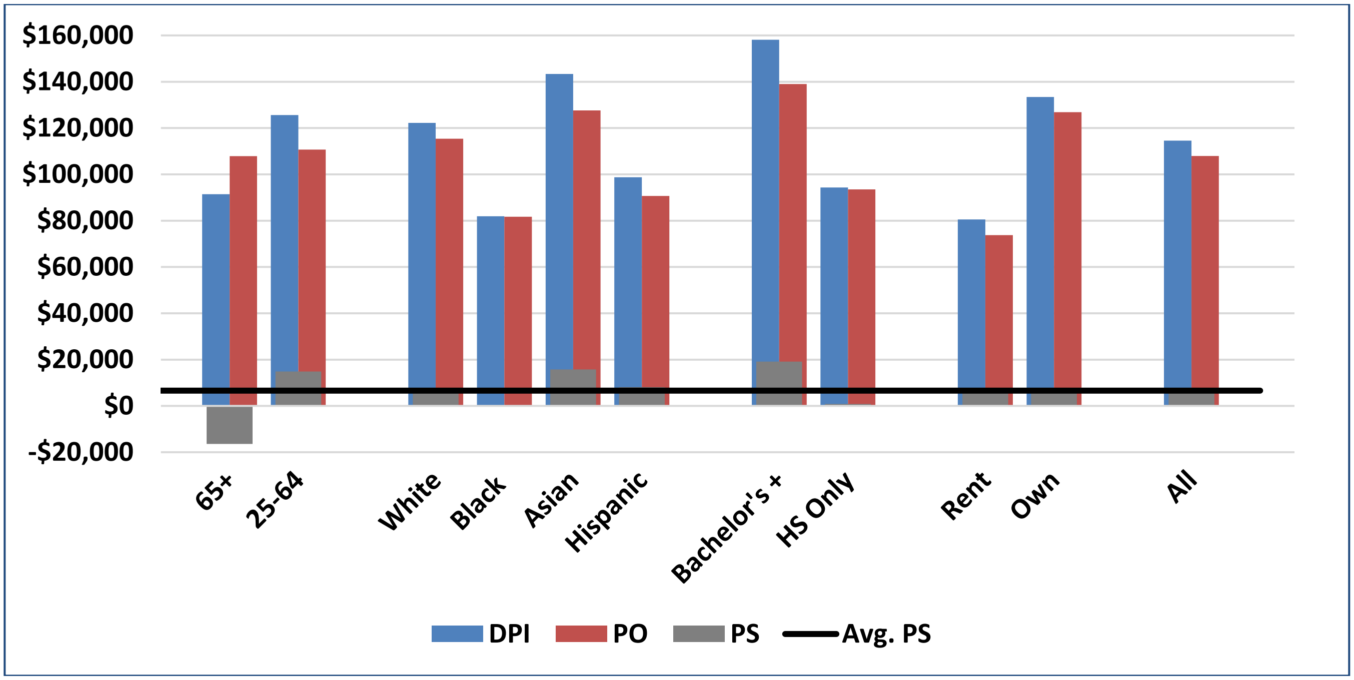
Figure 4: Distribution of Personal Savings (PS) by Eq. DPI





Notes: Figure 4a ranks all households by equivalized DPI decile and then shows the respective shares of DPI, PCE, and PS for each decile. Figure 4b shows the distribution of PS by equivalized DPI quintile, in $2017, for 2004-2022.

Figure 5: Average DPI, PO, and PS by Group (2017)



Notes: This figure shows the average DPI, Personal Outlays (PCE + Outlays), and PS for each demographic group. Age is defined as age of the householder. Race is assigned as in Census groupings (with Hispanic allocated to Race). The "other" group is omitted. Education is split into those with at least a bachelor's degree (including master's and PhD), and those with a high school diploma. The less than high school group is omitted. Housing tenure is split into renters and owners. The horizontal line represents the average PS for the full sample.

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Appendix Tables and Figures

Table A1: Constructing a Comparable Income across the CE and CPS for Linking

NIPA Table and Line	NIPA Categories	CPS ASEC Variables	CE Variables
Table 2.1, line 3	Wages and Salaries	hwsval	fsalarym
Table 2.1, line 10 + 11	Self-employment	hseval, hfrval	fsmpfrxm
Table 7.9, line 2	Net Rental Income	hrntval	Netrentm
Table 2.9, line 27:28	Interest and Dividends	hintval, hdivval	intrdvxm
Table 3.12, line 5	Social Security	hssval	frretirm
Table 3.12, line 23 + 36	Supplemental Security Income	hssival	fssixm
Table 3.12, line 7 + 14 +17	Unemployment Insurance + Veteran's Benefits	hucval, hvetval	othregxm
Internal table	Earned Income Tax Credit*	eit_cred	from TAXSIM (TTX2 file)
Internal table	Child Tax Credit*	ctc_crd + actc_crd	from TAXSIM (TTX2 file)
Internal table	Welfare + WIC + Food Stamps	hpawval, hfdval, hrnumwic	jfs_amtm, welfarem, fam_size

Notes: This table shows the NIPA items used to create comparable income and the CPS & CE variables from 2017 that correspond to those. Other years use similar information where there has been a survey change and these variables are not available. *For 2013-2022 only, as the CE did not implement TAXSIM in prior years.

Table A2a: Components of Disposable Personal Income by Decile (2017)

Category	Total ($B)	% of PI	0-10%	10-20%	20-30%	30-40%	40-50%	50-60%	60-70%	70-80%	80-90%	90-100%
Compensation of employees	$10,424	62.6%	1.0%	2.7%	3.6%	4.8%	6.1%	8.2%	10.9%	13.6%	17.9%	31.3%
Proprietors' income with inventory valuation	$1,429	8.6%	-0.2%	0.2%	0.3%	0.5%	1.0%	1.7%	2.9%	4.9%	9.2%	79.5%
Rental income of households with capital consumption adjustment	$633	3.8%	1.7%	4.0%	5.5%	6.5%	7.9%	9.0%	10.1%	12.7%	15.2%	27.4%
Household income receipts on assets	$2,555	15.3%	0.5%	0.8%	1.2%	1.8%	2.9%	4.2%	5.9%	8.7%	14.0%	60.2%
Household interest income	$1,446	8.7%	0.7%	1.1%	1.5%	2.3%	3.7%	5.1%	7.0%	9.8%	15.6%	53.3%
Household dividend income	$1,109	6.7%	0.2%	0.4%	0.7%	1.1%	1.9%	3.0%	4.5%	7.2%	11.7%	69.3%
Household current transfer receipts	$2,919	17.5%	6.9%	10.0%	11.5%	12.0%	11.9%	11.5%	9.9%	9.2%	8.7%	8.5%
Government social benefits	$2,784	16.7%	6.6%	10.2%	11.8%	12.2%	12.2%	11.5%	10.0%	9.1%	8.5%	8.1%
From business (net)	$29	0.2%	1.8%	3.5%	4.4%	5.2%	6.3%	7.6%	9.2%	11.3%	14.8%	36.0%
From nonprofit institutions	$106	0.6%	16.4%	6.0%	6.3%	8.3%	5.9%	10.4%	8.3%	13.1%	12.2%	13.2%
Less: Contributions for government social insurance, domestic	$1,299	7.8%	0.9%	2.8%	3.7%	4.8%	6.1%	8.2%	11.0%	13.9%	18.4%	30.0%
Household income	$16,662	100.0%	1.9%	3.5%	4.4%	5.3%	6.3%	7.6%	9.2%	11.3%	14.8%	35.8%
Personal income	**$16,663**	**100.0%**	**1.8%**	**3.5%**	**4.4%**	**5.2%**	**6.3%**	**7.6%**	**9.2%**	**11.3%**	**14.8%**	**36.0%**
Less: Taxes	$2,049	12.3%	0.3%	0.8%	1.2%	1.9%	2.9%	4.5%	6.8%	9.9%	15.6%	56.3%
Disposable personal income	**$14,614**	**87.7%**	**2.0%**	**3.9%**	**4.9%**	**5.7%**	**6.8%**	**8.0%**	**9.6%**	**11.4%**	**14.7%**	**33.1%**

Table A2b: DPI Inequality Metrics

Inequality Metric	2004	2005	2006	2007	2008	2009	2010	2011	2012
Mean ($2017)	$99,108	$99,357	$101,521	$103,217	$104,490	$104,418	$105,368	$105,507	$107,184
Median ($2017)	$71,956	$71,965	$72,561	$74,788	$75,589	$76,369	$77,998	$76,231	$76,325
0-20% Share	5.6%	5.5%	5.8%	5.8%	5.8%	5.9%	5.9%	5.8%	5.7%
20-40% Share	10.4%	10.4%	10.4%	10.5%	10.4%	10.7%	10.9%	10.6%	10.4%
40-60% Share	14.9%	14.9%	14.7%	14.9%	14.9%	14.9%	15.1%	14.8%	14.6%
60-80% Share	21.4%	21.3%	21.0%	21.3%	21.2%	21.4%	21.3%	21.1%	20.9%
80-100% Share	47.8%	47.9%	48.1%	47.5%	47.7%	47.1%	46.8%	47.7%	48.3%
Top 1% Share	11.4%	11.3%	12.2%	11.4%	11.3%	10.7%	10.8%	11.6%	12.4%
Top 5% Share	23.2%	23.2%	23.8%	23.2%	23.2%	22.5%	22.4%	23.5%	24.1%
Gini Index	0.416	0.415	0.416	0.411	0.412	0.408	0.404	0.413	0.419
90/10 Ratio	5.26	5.31	5.08	5.08	5.05	5.19	5.05	5.1	5.18

Inequality Metric	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Mean ($2017)	$105,221	$107,425	$110,544	$112,278	$114,542	$117,693	$121,503	$127,723	$130,427	$122,412
Median ($2017)	$77,065	$77,347	$80,177	$81,128	$82,370	$85,044	$88,327	$94,484	$97,247	$88,665
0-20% Share	5.8%	5.6%	5.9%	5.9%	5.9%	5.8%	5.8%	6.1%	6.1%	5.8%
20-40% Share	10.6%	10.6%	10.6%	10.7%	10.6%	10.6%	10.6%	11.0%	11.1%	10.7%
40-60% Share	15.0%	14.8%	14.9%	14.8%	14.8%	14.9%	15.0%	15.2%	15.4%	14.9%
60-80% Share	21.2%	21.1%	21.2%	21.0%	21.0%	20.9%	21.2%	21.1%	21.0%	20.6%
80-100% Share	47.4%	47.9%	47.4%	47.6%	47.8%	47.9%	47.5%	46.7%	46.4%	47.9%
Top 1% Share	11.4%	11.7%	11.5%	11.3%	11.5%	11.7%	11.1%	10.9%	11.2%	[11.3%-12.1%]
Top 5% Share	23.1%	23.3%	23.2%	23.2%	23.2%	23.6%	22.9%	22.3%	22.7%	[23.6%-24.2%]
Gini Index	0.407	0.412	0.405	0.403	0.411	0.410	0.400	0.385	0.383	0.399
90/10 Ratio	5.06	5.15	4.92	4.86	4.9	4.87	4.84	4.45	4.15	4.61

Notes: These tables are reprinted from the BEA website from the December 2022 release. For full methodology and details, please see the BEA landing page.

Table A3a: Personal Consumption Expenditures by Major Type of Product and Decile (2017)

Category	**Total ($B)**	**% of PCE**	**0-10%**	**10-20%**	**20-30%**	**30-40%**	**40-50%**	**50-60%**	**60-70%**	**70-80%**	**80-90%**	**90-100%**
Goods	4,212	32%	3.7%	5.3%	6.0%	7.0%	7.7%	8.9%	9.9%	11.3%	13.7%	26.5%
Durable goods	1,416	11%	1.3%	2.4%	2.8%	4.2%	4.7%	6.8%	8.3%	11.0%	16.5%	42.0%
Motor vehicles & parts	529	4%	0.3%	0.8%	0.9%	2.8%	2.7%	6.1%	7.4%	12.3%	18.8%	47.9%
Furnishings & durable household equip	319	2%	2.2%	3.7%	4.8%	6.0%	7.7%	8.6%	11.4%	12.5%	15.1%	28.1%
Recreational goods & vehicles	376	3%	1.4%	2.5%	2.8%	3.5%	3.8%	5.2%	6.0%	7.7%	14.6%	52.4%
Other durables	192	1%	2.4%	4.5%	5.2%	6.5%	6.7%	8.6%	10.0%	11.5%	15.8%	28.9%
Nondurable goods	2,796	21%	5.0%	6.7%	7.6%	8.4%	9.2%	9.9%	10.7%	11.4%	12.3%	18.7%
Food & beverages for off-premises cons	1,010	8%	6.4%	7.7%	8.4%	8.8%	9.1%	9.7%	10.4%	10.6%	11.5%	17.4%
Clothing & footwear	401	3%	4.8%	6.1%	6.9%	7.5%	8.6%	9.4%	10.5%	11.6%	12.9%	21.7%
Gasoline & other energy	324	2%	4.8%	7.5%	8.0%	8.5%	9.3%	10.1%	10.8%	10.9%	12.4%	17.7%
Other	1,061	8%	3.7%	5.8%	7.0%	8.2%	9.4%	10.3%	11.1%	12.3%	12.9%	19.1%
Services	9,078	68%	3.3%	5.0%	6.1%	6.8%	7.8%	8.6%	9.8%	11.2%	13.4%	28.1%
Household consumption expenditures	8,682	65%	3.3%	5.0%	6.1%	6.8%	7.8%	8.6%	9.8%	11.2%	13.4%	28.1%
Housing & utilities	2,350	18%	3.8%	5.3%	6.0%	6.6%	7.5%	8.3%	9.6%	11.2%	13.0%	28.6%
Health care	2,245	17%	3.9%	6.7%	8.5%	9.8%	9.9%	10.5%	10.9%	11.1%	11.7%	17.1%
Transportation	429	3%	2.8%	4.0%	5.0%	6.1%	7.3%	8.5%	10.3%	12.9%	14.5%	28.5%
Recreation	555	4%	2.0%	3.3%	4.3%	5.1%	6.5%	7.9%	9.3%	12.1%	15.6%	33.7%
Food & accommodations	913	7%	3.0%	4.1%	4.9%	5.5%	6.9%	7.8%	9.6%	11.4%	15.2%	31.6%
Financial services & insurance	1,073	8%	2.0%	3.4%	4.4%	5.0%	6.5%	7.3%	9.2%	10.7%	13.7%	37.8%
Other	1,115	8%	3.1%	4.4%	5.4%	5.5%	6.7%	7.8%	8.7%	10.3%	14.3%	33.9%
NPISH	396	3%	3.4%	5.1%	6.1%	6.9%	7.7%	8.7%	9.8%	11.2%	13.5%	27.6%
PCE less NPISH	12,894	97%	3.4%	5.1%	6.1%	6.9%	7.7%	8.7%	9.8%	11.2%	13.5%	27.6%
Personal Consumption Expenditures (PCE)	**13,291**	**100%**	**3.4%**	**5.1%**	**6.1%**	**6.9%**	**7.7%**	**8.7%**	**9.8%**	**11.2%**	**13.5%**	**27.6%**

Table A3b: PCE Inequality Metrics

Inequality Metric	2004	2005	2006	2007	2008	2009	2010	2011	2012
Mean ($2017)	$88,889	$91,085	$92,604	$93,686	$93,485	$92,035	$93,762	$94,588	$94,100
Median ($2017)	$70,124	$73,078	$74,484	$74,442	$75,029	$73,300	$75,984	$76,658	$75,672
0-20% Share	8.3%	8.5%	8.5%	8.4%	8.5%	8.6%	8.8%	8.9%	8.5%
20-40% Share	12.4%	12.8%	12.8%	12.8%	13.0%	13.0%	13.1%	13.1%	13.1%
40-60% Share	16.2%	16.3%	16.5%	16.3%	16.5%	16.2%	16.3%	16.4%	16.5%
60-80% Share	21.4%	21.1%	21.0%	20.9%	20.8%	21.0%	21.2%	21.1%	21.1%
80-100% Share	41.8%	41.3%	41.1%	41.6%	41.3%	41.2%	40.6%	40.6%	40.9%
Top 1% Share	9.0%	8.8%	8.8%	8.5%	9.1%	8.8%	8.4%	8.6%	8.4%
Top 5% Share	19.6%	19.2%	19.2%	19.3%	19.5%	19.4%	18.7%	18.8%	19.0%
Gini Index	0.336	0.329	0.331	0.332	0.335	0.330	0.327	0.323	0.331
90/10 Ratio	3.74	3.76	3.71	3.74	3.66	3.62	3.70	3.64	3.71

Inequality Metric	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Mean ($2017)	$94,663	$96,472	$98,511	$100,022	$102,371	$104,097	$105,489	$103,326	$110,407	$112,621
Median ($2017)	$75,917	$77,060	$79,427	$80,157	$82,838	$83,268	$84,650	$84,282	$87,737	$90,677
0-20% Share	8.5%	8.5%	8.7%	8.6%	8.5%	8.5%	8.9%	9.4%	8.9%	8.8%
20-40% Share	13.0%	12.8%	12.8%	12.9%	12.9%	12.9%	13.1%	13.5%	12.8%	13.1%
40-60% Share	16.4%	16.5%	16.4%	16.2%	16.4%	16.2%	16.5%	16.7%	16.3%	16.4%
60-80% Share	21.1%	20.9%	21.0%	21.0%	21.0%	21.1%	21.0%	20.7%	20.6%	21.0%
80-100% Share	41.0%	41.4%	41.2%	41.3%	41.1%	41.3%	40.6%	39.7%	41.3%	40.7%
Top 1% Share	8.6%	8.7%	8.5%	8.7%	8.8%	8.7%	8.8%	8.0%	9.1%	8.8%
Top 5% Share	19.0%	19.2%	19.2%	19.4%	19.3%	19.3%	19.3%	18.4%	19.8%	18.9%
Gini Index	0.329	0.335	0.330	0.331	0.332	0.333	0.325	0.311	0.320	0.326
90/10 Ratio	3.76	3.72	3.59	3.66	3.64	3.63	3.45	3.30	3.42	3.43

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Table A3c: Summary Statistics for PCE by Category (2017)

Category	Total ($B)	Mean	Median
Personal Consumption Expenditures (PCE)	**13,291**	**104,170**	**83,729**
Goods	4,212	33,015	24,787
Durable goods	1,416	11,098	3,475
Motor vehicles & parts	529	4,149	0
Furnishings & durable household equipment	319	2,502	999
Recreational goods & vehicles	376	2,945	361
Other durables	192	1,502	323
Nondurable goods	2,796	21,917	19,451
Food & beverages for off-premises consumption	1,010	7,920	6,816
Clothing & footwear	401	3,144	2,389
Gasoline & other energy	324	2,539	1,987
Other	1,061	8,314	6,941
Services	9,078	71,155	56,258
Household cons expenditures	8,682	68,048	53,707
Housing & utilities	2,350	18,420	13,696
Health care	2,245	17,598	14,701
Transportation	429	3,366	1,834
Recreation	555	4,352	2,555
Food & accommodations	913	7,158	4,397
Financial services & insurance	1,073	8,412	4,385
Other	1,115	8,743	4,710
NPISH	396	3,107	2,518
Comparable Income (Constructed for the Exercise)	*13,357*	100,647	61,836
Personal Income	**16,663**	**130,600**	**90,001**
Disposable Personal Income	**14,614**	**114,542**	**82,042**

Notes: These tables resemble tables from the BLS website. For full methodology and details, please see the BLS landing page, though the methodology has been updated since the December 2022 release. Real values are based on PCE price index

Table A4: PCE Shares by Decile of Eq. DPI (2017)

Category	**0-10%**	**10-20%**	**20-30%**	**30-40%**	**40-50%**	**50-60%**	**60-70%**	**70-80%**	**80-90%**	**90-100%**
Goods	4.9%	5.9%	6.7%	7.7%	8.8%	9.7%	10.6%	11.9%	14.1%	19.7%
Durable goods	3.3%	4.2%	5.0%	6.4%	7.9%	9.2%	10.4%	12.3%	16.4%	24.8%
Motor vehicles & parts	3.1%	4.5%	5.3%	6.7%	8.2%	9.3%	10.8%	12.6%	14.7%	24.9%
Furnishings & durable household equip	3.5%	4.4%	5.5%	6.7%	7.9%	9.4%	11.1%	13.0%	15.6%	22.9%
Recreational goods & vehicles	2.6%	3.2%	3.8%	5.4%	7.4%	9.0%	9.5%	12.2%	20.4%	26.5%
Other durables	4.7%	5.1%	6.0%	7.4%	8.3%	9.0%	9.8%	10.9%	14.6%	24.3%
Nondurable goods	5.7%	6.7%	7.6%	8.4%	9.2%	10.0%	10.8%	11.6%	12.9%	17.1%
Food & beverages for off-premises cons	6.7%	7.5%	8.0%	8.6%	9.3%	9.9%	10.5%	11.1%	12.1%	16.3%
Clothing & footwear	4.7%	5.7%	6.3%	7.0%	7.9%	9.1%	10.4%	12.1%	14.8%	21.9%
Gasoline & other energy	5.2%	6.3%	7.3%	8.3%	9.4%	10.4%	11.6%	12.6%	13.3%	15.6%
Other	5.3%	6.6%	7.7%	8.7%	9.5%	10.3%	10.9%	11.8%	12.8%	16.5%
Services	4.7%	5.6%	6.5%	7.4%	8.4%	9.4%	10.3%	11.5%	14.1%	22.2%
Household cons expenditures	4.6%	5.5%	6.5%	7.4%	8.4%	9.4%	10.3%	11.5%	14.1%	22.2%
Housing & utilities	5.2%	5.7%	6.5%	7.3%	8.1%	9.0%	10.2%	11.3%	14.0%	22.8%
Health care	5.1%	7.3%	8.6%	9.5%	10.2%	11.0%	10.9%	11.3%	11.8%	14.3%
Transportation	4.3%	5.0%	5.8%	6.9%	8.2%	9.2%	10.4%	11.9%	14.6%	23.8%
Recreation	4.0%	4.4%	5.2%	6.0%	7.2%	8.3%	9.7%	11.8%	15.9%	27.5%
Food & accommodations	4.2%	4.4%	5.1%	6.1%	7.4%	8.8%	10.3%	11.9%	15.3%	26.5%
Financial services & insurance	3.1%	4.0%	5.2%	6.3%	7.9%	8.8%	10.0%	11.8%	16.8%	26.1%
Other	4.9%	4.8%	5.6%	6.4%	7.5%	8.6%	9.8%	11.3%	14.7%	26.5%
PCE less NPISH	4.7%	5.7%	6.6%	7.5%	8.5%	9.5%	10.4%	11.6%	14.1%	21.4%
NPISH	5.4%	6.2%	6.9%	7.6%	8.5%	9.3%	10.2%	11.3%	13.7%	20.9%
Personal Consumption Expenditures (PCE)	**4.7%**	**5.7%**	**6.6%**	**7.5%**	**8.5%**	**9.5%**	**10.4%**	**11.6%**	**14.1%**	**21.4%**

Notes: This table is shares of PCE, ranked on equivalized Disposable Personal Income, and calculated in the CPS.

Table A5: PCE Shares by Decile of Eq. PI (2017)

Category	0-10%	10-20%	20-30%	30-40%	40-50%	50-60%	60-70%	70-80%	80-90%	90-100%
Personal Consumption Expenditures (PCE)	**4.8%**	**5.7%**	**6.6%**	**7.6%**	**8.6%**	**9.5%**	**10.4%**	**11.5%**	**14.0%**	**21.3%**
Goods	4.9%	5.8%	6.7%	7.8%	8.8%	9.7%	10.7%	11.8%	14.1%	19.7%
Durable goods	3.2%	4.1%	5.0%	6.6%	8.0%	9.0%	10.5%	12.1%	16.5%	24.8%
Motor vehicles & parts	3.0%	4.3%	5.4%	6.9%	8.2%	9.4%	11.1%	12.1%	14.7%	24.9%
Furnishings & durable household equipment	3.5%	4.4%	5.3%	6.7%	8.1%	9.3%	11.2%	12.8%	15.8%	22.9%
Recreational goods & vehicles	2.6%	3.0%	3.7%	5.9%	7.5%	8.4%	9.6%	12.2%	20.6%	26.5%
Other durables	4.7%	5.0%	6.1%	7.4%	8.5%	8.9%	9.6%	10.8%	14.6%	24.3%
Nondurable goods	5.7%	6.7%	7.6%	8.4%	9.2%	10.0%	10.8%	11.6%	12.9%	17.1%
Food & beverages for off-premises consumption	6.7%	7.4%	8.0%	8.6%	9.3%	10.0%	10.5%	11.0%	12.1%	16.4%
Clothing & footwear	4.7%	5.6%	6.3%	7.0%	7.9%	9.1%	10.5%	11.9%	14.9%	22.0%
Gasoline & other energy	5.2%	6.2%	7.3%	8.2%	9.4%	10.6%	11.7%	12.5%	13.3%	15.5%
Other	5.3%	6.6%	7.7%	8.8%	9.7%	10.3%	10.8%	11.7%	12.6%	16.4%
Services	4.7%	5.6%	6.6%	7.5%	8.5%	9.4%	10.2%	11.3%	14.0%	22.1%
Household cons expenditures	4.7%	5.6%	6.6%	7.5%	8.5%	9.4%	10.2%	11.4%	14.0%	22.2%
Housing & utilities	5.2%	5.7%	6.5%	7.4%	8.1%	9.1%	10.1%	11.3%	14.0%	22.6%
Health care	5.3%	7.6%	8.9%	9.8%	10.4%	10.8%	10.8%	11.1%	11.3%	14.0%
Transportation	4.3%	4.9%	5.7%	6.9%	8.1%	9.3%	10.4%	11.7%	14.6%	24.0%
Recreation	4.0%	4.4%	5.2%	6.0%	7.1%	8.3%	9.7%	11.7%	15.9%	27.6%
Food & accommodations	4.1%	4.4%	5.1%	6.1%	7.3%	8.9%	10.3%	11.8%	15.4%	26.7%
Financial services & insurance	3.1%	4.0%	5.2%	6.5%	7.9%	9.0%	9.7%	11.7%	16.8%	26.1%
Other	4.9%	4.7%	5.5%	6.4%	7.4%	8.7%	9.8%	11.1%	14.6%	26.7%
NPISH	5.4%	6.1%	6.9%	7.7%	8.5%	9.3%	10.1%	11.2%	13.7%	21.0%

Notes: This table represents the distribution of PCE, when ranked on equivalized personal income (PI), rather than equivalized PCE or equivalized DPI.

Table A6: PI and PCE Matrix (2017)

Equivalized Disposable Personal Income Quantiles	Equivalized Personal Consumption Expenditure Quantiles											
	0-10%	**10-20%**	**20-30%**	**30-40%**	**40-50%**	**50-60%**	**60-70%**	**70-80%**	**80-90%**	**90-100%**	**Top 5%**	**Top 1%**
						(a) Share of Households						
0-10%	4.4%	1.8%	1.1%	0.7%	0.5%	0.4%	0.4%	0.3%	0.3%	0.1%	0.0%	0.0%
10-20%	2.6%	2.3%	1.6%	1.1%	0.8%	0.6%	0.4%	0.3%	0.2%	0.1%	0.0%	0.0%
20-30%	1.2%	2.0%	1.8%	1.5%	1.2%	0.8%	0.6%	0.4%	0.3%	0.2%	0.0%	0.0%
30-40%	0.7%	1.4%	1.6%	1.6%	1.4%	1.1%	0.9%	0.6%	0.5%	0.3%	0.1%	0.0%
40-50%	0.4%	0.9%	1.3%	1.5%	1.5%	1.3%	1.1%	0.9%	0.6%	0.4%	0.2%	0.0%
50-60%	0.3%	0.6%	0.9%	1.3%	1.4%	1.6%	1.4%	1.1%	0.8%	0.6%	0.2%	0.0%
60-70%	0.2%	0.5%	0.7%	1.0%	1.3%	1.5%	1.5%	1.4%	1.1%	0.8%	0.3%	0.0%
70-80%	0.1%	0.3%	0.5%	0.7%	1.0%	1.3%	1.6%	1.8%	1.6%	1.1%	0.5%	0.1%
80-90%	0.1%	0.2%	0.3%	0.5%	0.7%	0.9%	1.3%	1.8%	2.2%	2.1%	1.0%	0.2%
90-100%	0.0%	0.1%	0.1%	0.2%	0.3%	0.5%	0.8%	1.3%	2.3%	4.3%	2.6%	0.7%
Top 5%	0.0%	0.0%	0.1%	0.1%	0.1%	0.2%	0.4%	0.6%	1.1%	2.4%	1.5%	0.4%
Top 1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.1%	0.2%	0.4%	0.3%	0.1%
						(b) Share of DPI						
0-10%	0.9%	0.4%	0.2%	0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.0%	0.0%	0.0%
10-20%	1.0%	0.9%	0.6%	0.4%	0.3%	0.2%	0.1%	0.1%	0.1%	0.0%	0.0%	0.0%
20-30%	0.7%	1.0%	0.9%	0.7%	0.5%	0.4%	0.3%	0.2%	0.1%	0.1%	0.0%	0.0%
30-40%	0.5%	0.9%	1.0%	0.9%	0.8%	0.6%	0.4%	0.3%	0.2%	0.1%	0.0%	0.0%
40-50%	0.3%	0.7%	1.0%	1.0%	1.0%	0.9%	0.7%	0.5%	0.4%	0.3%	0.1%	0.0%
50-60%	0.3%	0.6%	0.8%	1.1%	1.2%	1.2%	1.1%	0.8%	0.6%	0.4%	0.2%	0.0%
60-70%	0.2%	0.5%	0.7%	1.0%	1.3%	1.4%	1.5%	1.3%	1.0%	0.7%	0.3%	0.0%
70-80%	0.2%	0.4%	0.6%	0.9%	1.2%	1.5%	1.9%	2.0%	1.7%	1.2%	0.5%	0.1%
80-90%	0.1%	0.3%	0.4%	0.7%	1.0%	1.4%	2.0%	2.6%	3.1%	3.0%	1.4%	0.3%
90-100%	0.2%	0.3%	0.5%	0.7%	1.0%	1.8%	2.9%	4.5%	7.4%	14.0%	8.7%	2.2%
Top 5%	0.1%	0.2%	0.3%	0.5%	0.7%	1.2%	1.9%	3.0%	5.0%	10.3%	6.5%	1.7%
Top 1%	0.1%	0.1%	0.2%	0.3%	0.4%	0.7%	1.1%	1.5%	2.4%	4.7%	2.9%	0.6%
						(c) Share of PCE						
0-10%	1.3%	0.8%	0.5%	0.4%	0.3%	0.3%	0.3%	0.3%	0.3%	0.2%	0.1%	0.0%
10-20%	0.9%	1.1%	0.9%	0.7%	0.5%	0.4%	0.3%	0.3%	0.3%	0.2%	0.0%	0.0%
20-30%	0.5%	1.0%	1.0%	1.0%	0.8%	0.6%	0.5%	0.4%	0.4%	0.3%	0.1%	0.0%
30-40%	0.3%	0.7%	1.0%	1.0%	1.0%	0.9%	0.8%	0.7%	0.6%	0.5%	0.3%	0.1%
40-50%	0.2%	0.5%	0.8%	1.0%	1.1%	1.1%	1.0%	0.9%	0.8%	0.9%	0.5%	0.2%
50-60%	0.1%	0.4%	0.6%	0.9%	1.2%	1.4%	1.4%	1.3%	1.0%	1.3%	0.7%	0.2%
60-70%	0.1%	0.3%	0.5%	0.8%	1.1%	1.4%	1.6%	1.6%	1.5%	1.7%	0.9%	0.2%
70-80%	0.1%	0.2%	0.3%	0.5%	0.8%	1.2%	1.7%	2.1%	2.2%	2.5%	1.4%	0.4%
80-90%	0.0%	0.1%	0.2%	0.3%	0.5%	0.9%	1.4%	2.2%	3.1%	5.3%	3.4%	1.2%
90-100%	0.0%	0.0%	0.1%	0.1%	0.2%	0.5%	0.9%	1.7%	3.4%	14.4%	11.4%	6.1%
Top 5%	0.0%	0.0%	0.0%	0.1%	0.1%	0.2%	0.4%	0.8%	1.6%	8.6%	7.0%	4.1%
Top 1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.2%	0.3%	1.5%	1.1%	0.6%

Notes: In panel (a), each cell represents the share of households in each PI & PCE quantile. In panel (b) each cell represents the share of PI for households in each PI & PCE quantile. In panel (c) each cell represents the share of PCE for households in each PI & PCE quantile. Each panel is constructed on a distribution ranked on equivalized DPI & PCE.

Table A7: Comparison with OECD results

Gindelsky and Martin (2024)

		Personal Consumption Expenditure Quintiles				
Personal Income Quintiles		0-20%	20-40%	40-60%	60-80%	80-100%
	0-20%	11.1%	4.5%	2.3%	1.4%	0.7%
	20-40%	5.3%	6.5%	4.5%	2.5%	1.3%
	40-60%	2.2%	5.0%	5.8%	4.5%	2.4%
	60-80%	1.1%	2.9%	5.1%	6.3%	4.6%
	80-100%	0.4%	1.1%	2.4%	5.2%	10.9%

OECD Results

		Consumption Expenditure Quintiles				
Income Quintiles		0-20%	20-40%	40-60%	60-80%	80-100%
	0-20%	10.3%	5.4%	2.8%	1.2%	0.3%
	20-40%	5.5%	5.4%	4.9%	3.1%	1.2%
	40-60%	2.8%	4.9%	5.2%	4.9%	2.3%
	60-80%	1.3%	3.4%	5.0%	5.6%	4.6%
	80-100%	0.2%	0.9%	2.1%	5.2%	11.6%

Notes: This figure compares the results in Table A6a, aggregated by quintile (equivalized), and compared to U.S. results in Balestra and Oehler (2023).

Table A8: Cross Shares of Households for those with Age <65, No Retirement Income, Not Enrolled, and DPI>0

		Personal Consumption Expenditure Quintiles				
Personal Income Quintiles		0-20%	20-40%	40-60%	60-80%	80-100%
	0-20%	12.7%	4.3%	1.9%	1.0%	0.5%
	20-40%	6.2%	6.3%	3.5%	1.6%	0.7%
	40-60%	2.8%	5.5%	5.5%	3.3%	1.4%
	60-80%	1.4%	3.5%	5.7%	6.3%	3.9%
	80-100%	0.4%	1.3%	2.9%	6.1%	11.3%

Notes: This table repeats Table 4a, aggregated by quintile, but tabulates only households with a reference person under 65 who reported no retirement income, were not enrolled in school, and who had positive DPI. The equivalized quintiles are still based on the full population, so the row and column sums are not balanced.

Table A9: Cross Shares using CE Income and Expenditures

		CE Expenditure Quintiles				
		0-20%	20-40%	40-60%	60-80%	80-100%
CE Income Quintiles	0-20%	11.00%	4.35%	2.14%	1.46%	1.06%
	20-40%	5.91%	6.26%	4.08%	2.19%	1.55%
	40-60%	2.33%	5.51%	5.94%	3.86%	2.37%
	60-80%	0.65%	3.12%	5.38%	6.74%	4.12%
	80-100%	0.12%	0.74%	2.48%	5.75%	10.90%

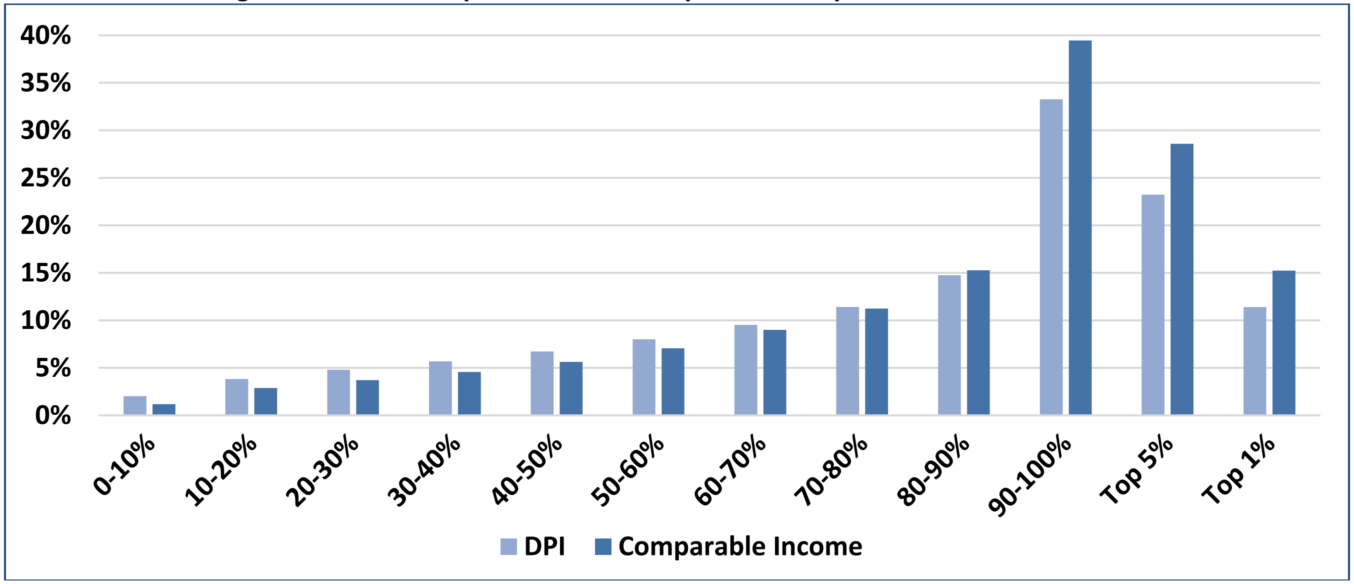
Notes: Using the CE sample of 8,238 underlying the distributional PCE estimates, this table computes the frequencies for quintiles of equivalized after-tax income and consumer expenditures as measured in the CE. After tax income is given by the variable FINATXEM, while expenditure is based on the variable ZTOTAL (after subtracting pension contributions and personal insurance as well as miscellaneous expenditures only collected in the last interview).

Table A10: Characteristics and Expenditures of the Bottom Quintile of Income in the CE Sample

	CE Expenditure Quintiles				
	0-20%	20-40%	40-60%	60-80%	80-100%
% Age 65+	28.7%	31.4%	37.3%	34.0%	47.2%
% White	49.2%	54.9%	67.5%	65.2%	80.3%
% Black	25.0%	19.2%	15.0%	10.1%	4.4%
% Asian	2.9%	5.8%	3.6%	8.9%	8.1%
% Hispanic	21.3%	16.9%	12.7%	14.8%	6.2%
% Bachelor's Degree +	7.5%	14.3%	22.4%	35.1%	59.2%
% Owning	32.7%	38.4%	50.3%	58.2%	71.5%
% Farm Income > $1000k	0.8%	0.6%	0.7%	0.9%	3.8%
Mean # of Self-Emp. Members	0.02	0.04	0.06	0.08	0.09
Mean Est. Home Value	129,464	181,786	216,733	299,077	343,285
Mean Income of Census Tract*	57,610	64,753	72,299	79,902	91,974
Mean Expenditures					
Total	15,598	26,286	33,674	49,548	86,792
Food	4,101	5,545	6,445	7,728	10,550
Housing	6,800	10,816	13,890	17,721	28,532
Apparel	421	637	649	1,027	1,571
Transportation	1,724	3,873	5,095	10,563	20,698
Health Care	1,177	2,065	3,249	4,919	7,110
Entertainment	557	987	1,425	2,434	4,567
Personal Care	91	157	231	340	568
Education	122	938	659	1,959	6,125
Cash Contributions	212	512	769	1,427	4,451
Other	393	756	1,262	1,430	2,619
Mean Financing for Vehicle Purch.	31	568	169	2,175	5,411

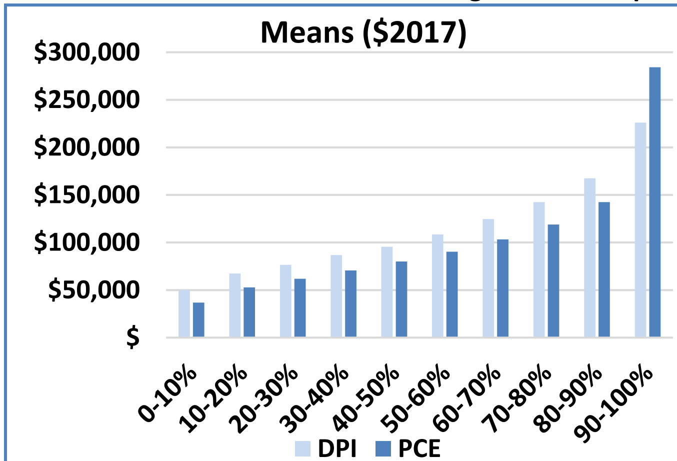
Notes: Using the CE sample of 8,238 underlying the distributional PCE estimates, this table computes statistics for quintiles of equivalized after-tax income and consumer expenditures as measured in the CE. After tax income is given by the variable FINATXEM, while expenditure is based on the variable ZTOTAL (after subtracting pension contributions and personal insurance as well as miscellaneous expenditures only collected in the last interview). Mean Income of the Census Tract is from the American Community Survey 5-year Estimates for 2017. Financing on vehicle purchasing includes cars, trucks, motorcycles, boats, recreational vehicles, and aircraft.

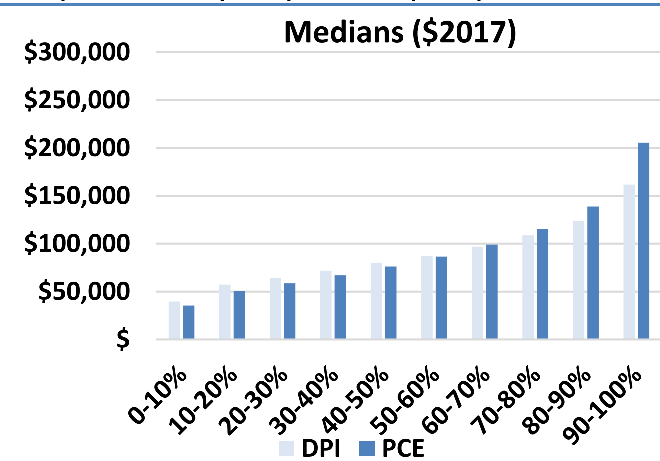
Figure A1: How Comparable Income represents Disposable Personal Income



Notes: This figure shows the shares of comparable income for each quantile, with data ranked on equivalized DPI.

Figure A2: Comparing Means and Medians (ranked on Eq. PCE) in levels (2017)

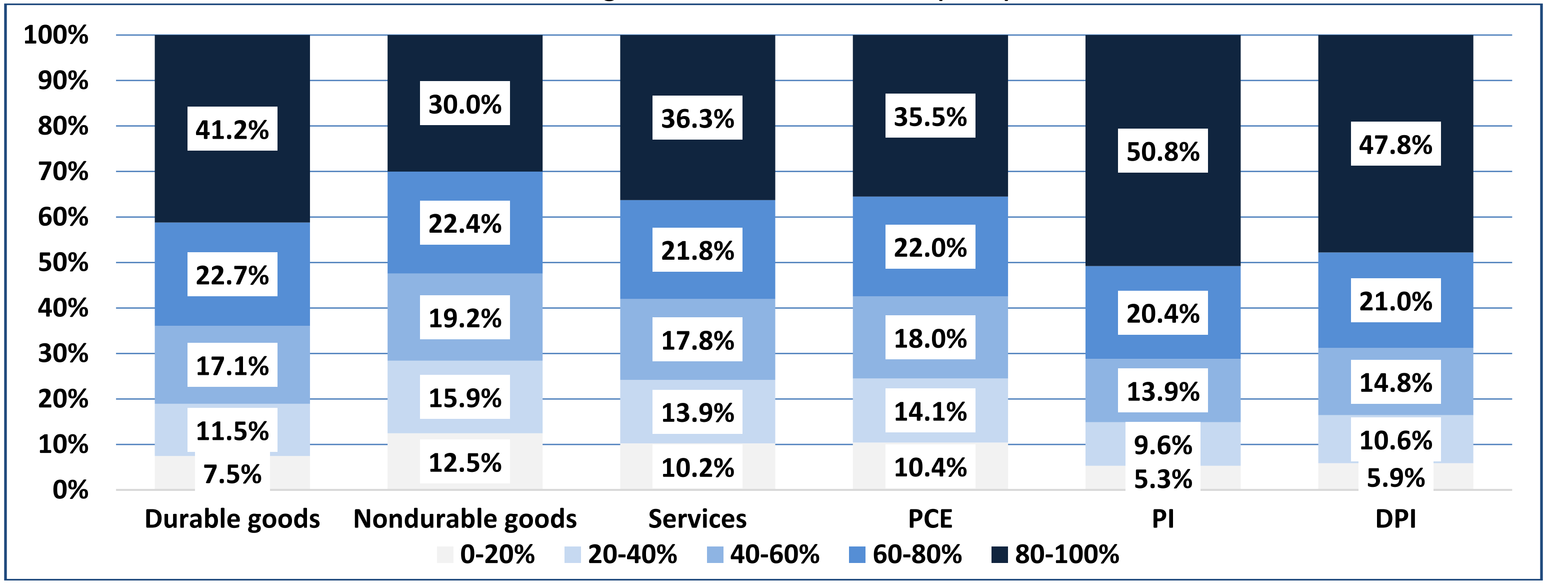




PCE Rank	Mean DPI	Mean PCE
Top 5%	$256,549	$392,175
Top 1%	$300,638	$871,545

Notes: This figure is the equivalent of Figure 2b, but ranked on equivalized PCE, rather than DPI

Figure A3: Quintile Breakout (2017)



Notes: This figure shows the quintile breakout within durable goods, nondurable goods, and services as disaggregated in PCE, along with the distributions of PCE, PI, and DPI.