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GRANULAR INCOME INEQUALITY AND MOBILITY USING IDDA: EXPLORING PATTERNS ACROSS RACE AND ETHNICITY

Illenin O. Kondo
Kevin Rinz
Natalie Gubbay
Brandon Hawkins
John L. Voorheis
Abigail K. Wozniak

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Granular Income Inequality and Mobility using IDDA: Exploring Patterns across Race and Ethnicity
Illenin O. Kondo, Kevin Rinz, Natalie Gubbay, Brandon Hawkins, John L. Voorheis, and Abigail K. Wozniak
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ABSTRACT

We explore the evolution of income inequality and mobility in the U.S. for a large number of subnational groups defined by race and ethnicity, using granular statistics describing income distributions, income mobility, and conditional income growth derived from the universe of tax filers and W-2 recipients that we observe over a two-decade period (1998–2019). We find that income inequality and income growth patterns identified from administrative tax records differ in important ways from those that one might identify in public survey sources. The full set of statistics that we construct is available publicly alongside this paper as the Income Distributions and Dynamics in America, or IDDA, dataset. Using two applications, we illustrate IDDA's relevance for understanding income inequality trends. First, we extend Bayer and Charles (2018) beyond earnings gaps between Black and White men and document that, unlike those for other groups, earnings for both Black men and Black women fell behind earnings for White men following the Great Recession. This trend lasted through 2019, the end of the data period. Second, we document a significant reversal in the convergence of earnings for Native earners in Native areas.

Illenin O. Kondo
Federal Reserve Bank of Minneapolis
90 Hennepin Avenue
Minneapolis, MN 55401
kondo@illenin.com

Kevin Rinz
Washington Center for Equitable Growth
740 15th St NW
8th Floor
Washington, DC 20005
krinz@equitablegrowth.org

Natalie Gubbay
Federal Reserve Bank of Minneapolis
90 Hennepin Avenue
Minneapolis, MN 55401
natalie.gubbay@mpls.frb.org

Brandon Hawkins
University of California, Davis
bmhawkins@ucdavis.edu

John L. Voorheis
U.S. Census Bureau
john.l.voorheis@census.gov

Abigail K. Wozniak
Federal Reserve Bank of Minneapolis
90 Hennepin Ave.
Minneapolis, MN 55401
and IZA
abigailwozniak@gmail.com

A data repository and technical documentation is available at
www.minneapolisfed.org/idda

1 Introduction

Earnings in the United States are significantly more unequal today than 50 years ago, when a multi-decade pattern of widely shared growth began to retreat. Since 1980, the pace of earnings growth has been uneven, and varying, for Americans throughout the earnings distribution. The course of widening earnings disparities has been well-documented, and a number of patterns and episodes have emerged (Hoffmann et al., 2020). The highest earners have experienced consistent growth in their earnings since 1980, although since about 2000, this has slowed or become more concentrated among the very highest earners (Kopczuk et al., 2010; Blanchet et al., 2022). Relative real earnings for workers below the median have fallen and partially recovered more than once (Autor et al., 2008; Blanchet et al., 2022; Autor et al., 2023). Although these patterns are robust, important differences across demographic groups—notably between women and men—have been documented (Guvenen et al., 2022).

A parallel literature has documented increases in inequality in broader measures of income after 1980 - for instance, tax-unit-level-adjusted gross income from IRS tax data or household income reported on surveys such as the Current Population Survey (Burkhauser et al., 2012; Piketty and Saez, 2003). While broad measures of inequality that are sensitive to the middle of the distribution (such as the Gini coefficient) have continued to increase at a measured pace, top income inequality (measured, for example, by the top 1 percent share of income) saw most of its increase before 2000 (Burkhauser et al., 2011). Over the period from 2000 through 2019, there has not been a clear trend in most top income inequality measures (Piketty et al., 2017; Auten and Splinter, 2024).[1]

In spite of this significant body of evidence, there is still much we do not know about how earnings and income have changed for many Americans over the last five decades of stubbornly rising inequality. The open questions are particularly acute at the subnational level. For example, have U.S. groups defined by race and ethnicity experienced the major episodes in changing income inequality in similar ways, or not? Questions about how income evolves over time for members of these groups have also been difficult to answer. Do low earners in all demographic groups move into higher earnings percentiles at the same rate? Do these patterns differ depending on the state

[1]Measuring inequality of broader income, particularly at the top of the distribution, is complicated by economy-wide changes in the structure of business ownership toward closely-held pass-through entities, now the dominant source of income for top earners. Assumptions about how to allocate unreported and untaxed income flowing through these pass-through entities have outsized importance for inferred trends in top income inequality (Smith et al., 2019).

where individuals live and work? Observing the evolution of income distributions for subnational groups like these is key for more fully understanding and, potentially, addressing U.S. earnings and income inequality, particularly in light of the non-uniform patterns identified in the literature.

Answering these questions requires data on income distributions and income mobility at high levels of granularity. We define a data source as having this granularity if measures of income distributions and dynamics are available in three dimensions: for many demographic groups, for geographic areas below the national level, and for intersections of the previous two dimensions. Yet, the availability of such data has been limited. In this paper, we construct and use a novel data source with extensive information in the three dimensions of granularity: the Income Distributions and Dynamics in America, or IDDA, data. IDDA has been made publicly available as part of this project.

Using IDDA, we first document patterns of income inequality in the U.S. as a whole that differ in some important ways from patterns identified in publicly available survey sources, although the patterns are similar at a high level. Our main comparison is with the Current Population Survey (CPS). Despite broadly similar aggregate patterns, we find that the CPS is inadequate for producing basic distributional statistics for many race and ethnicity groups at the state level.[2] Moreover, the material differences between the distributional patterns produced by IDDA and the CPS at the national level suggest that researchers would benefit from using IDDA as a reference when studying inequality for race and ethnicity groups, and other groups, even at this highly aggregate level.

To illustrate the relevance of granular approaches to studying income and earnings inequality in U.S. race and ethnicity groups, we extend comparisons in a key paper on earnings convergence for Black and White men (Bayer and Charles, 2018, henceforth BC) to more recent years, more top percentiles, and more granular race and ethnicity groups using IDDA. We show a unique receding pattern for Black men and Black women between 2005 and 2019, relative to White men. Across the earnings distribution, earnings for both groups fell further behind earnings for White men. The divergence begins following the Great Recession and continues through the end of the data period. Over this period, relative to White men, earnings for men in other race and ethnicity groups, for women in other race and ethnicity groups, or for White women do not consistently lose ground.

[2] Appendix material reveals similar issues with measuring some subnational distributions using the American Community Survey (ACS).

We then ask, what income dynamics patterns accompanied the development of inequality that we observed? This analysis leverages the longitudinal dimension of the administrative data underlying IDDA statistics on income mobility and income changes by demographic group. As we did with the distributional measures, we begin by documenting how changes in incomes reported in IDDA compare with income dynamics constructed using survey-based, public-use data. Do those differ across population subgroups, such as those defined by race and ethnicity or initial income? We find that the distribution of earnings growth as estimated using public-use survey data is more spread out relative to the distribution estimated using IDDA, and survey-based estimates are substantially more variable within groups. This noise obscures differences in earnings growth across groups, but IDDA data point to consistent differences in earnings growth across groups defined by race and ethnicity. Asian and White earners typically see faster growth, while Black and American Indian or Alaska Native earners see slower growth, especially over longer horizons.

Finally, we document earnings and income patterns for individuals living in Native areas, which include American Indian reservations, trust lands, and other Native geographies as delineated by the Census Bureau. We find that since the Great Recession, earnings have fallen for Native earners living in Native areas relative to American Indian or Alaska Native earners throughout the U.S. Combined, our analysis of income distributions and dynamics for U.S. race and ethnicity groups suggests that relative earnings can evolve quite differently across groups during a given time period. Moreover, this evolution can vary across locations and at different earnings percentiles.

To answer our research questions, we compiled the Income Distribution and Dynamics in America granular data set, or IDDA, alongside this paper. IDDA is built from the universe of tax records matched to internal Census Bureau demographic information for the period 1998 to 2019. It reflects the experiences of the populations of U.S. tax filers and W-2 employees over this period. Broadly, we tabulate statistics from individual-level tax records to describe the distribution of incomes and movements through it over time for a large set of demographic groups. More precisely, we compute statistics for groups defined by four elements: income source and unit; U.S. or individual states; year; and demographic groups defined by age bins, sex, race, ethnicity, birthplace (U.S. or abroad), and intersections of the demographic groups. Within each group, we calculate two types of statistics. The first type characterizes the distribution of incomes for a group in several ways. These include percentile values ranging from the 10th percentile to the top 99.999th percentile for the group; shares of income going to top earners; and shares of the group among all top earners at a point in time. The second type characterizes the mobility of incomes in the group across income distribution bins over time, as well as the distribution of income changes experienced starting from a given initial income distribution bin.

We developed this novel resource to answer our questions because even large surveys like the American Community Survey (ACS) may capture samples that are small in absolute terms for groups that constitute small shares of the population (either nationally or in a specific place). Such samples may not support reliable estimates that describe the full distribution of income. Surveys also tend not to follow respondents over time, thereby making it difficult to use them to understand income dynamics, or they trade off cross-sectional sample size against panel duration, limiting the granularity of any income dynamics estimates that may be producible. Moreover, measuring top incomes well is critical for understanding inequality, but measures based on surveys can be distorted by both disclosure avoidance procedures (e.g., topcoding) and survey misreporting (Burkhauser et al., 2011; Bee and Mitchell, 2017; Bee et al., 2023).

Such data issues are particularly important when it comes to understanding differences in income inequality and dynamics across groups defined by race and ethnicity, as these groups are unevenly distributed across space and differentially likely to be affected by measurement issues related to top incomes. It is especially important to be aware of differences in the prevalence of groups across space in this context, as state income distributions have become less similar to each other at the top in recent decades, and this phenomenon appears to be driven by the top of the White income distribution (Rinz and Voorheis, 2023).

This paper and the underlying data construction contribute to a growing field in which administrative sources are leveraged to understand detailed distributional patterns in the U.S. economy while also sharing aggregate data so that other researchers may more quickly innovate.[3] Chetty et al. (2014) analyze measures of intergenerational income mobility by location of residence for a cohort of individuals born in the early 1980s and make their data available via their Opportunity Atlas portal (Chetty et al., 2018). Blanchet et al. (2022) analyze shares of income and economic growth accruing in the most recent daily period to U.S. earners by percentile, and they make their method available on their Realtime Inequality site. In a recent issue of *Quantitative Economics*, multiple

[3]We facilitate public access to IDDA through this website.

papers explored detailed country-level inequality data constructed from administrative data from 13 countries and released as the Global Repository of Income Dynamics Repository (GRID).[4] Additionally, the Census Bureau's Mobility, Opportunity and Volatility Statistics and National Experimental Wellbeing Statistics projects will produce public data products measuring income inequality, poverty, and income mobility using linked survey, Census, and administrative data.[5]

Relative to these efforts, IDDA offers several advantages for studying subnational patterns in labor market earnings and incomes for its populations of U.S. tax filers and W-2 employees. First, our data are granular: IDDA includes a wide range of statistics for national and subnational geographic areas (states) as well as many subnational demographic populations. Second, we combine measurement of income changes and mobility with measurement of income distributions from a single source for our populations of interest. And third, the statistics that underlie our analysis are computed directly from the universe of tax information, which means we do not need to rely on modeling assumptions to link micro and macro data sources.

These features are especially important for producing granular measures characterizing experiences across income distributions and income dynamics across groups defined by place, income rank, and demographic characteristics such as gender, age, U.S.-birth status, race and ethnicity, or their intersections. Measuring such experiences can be very demanding in terms of the number of observations required, and relying on samples generated by even large surveys like the ACS can leave some groups without estimates for most places and most groups without estimates for some places, as we will show. Even when it is possible to construct estimates of distributional features from public survey data, they are often extremely noisy. Combining survey and administrative data, as we do in this project, substantially expands the set of groups and places that can be included, as well as the possible measures that can be produced. Akee et al. (2019) use these linkages at the U.S. level to document differences across race and ethnicity groups in incomes, top income shares, and income mobility. Rinz and Voorheis (2023) also leverage these linkages at the subnational level for tax units to discuss large differences in income growth across race and ethnicity groups within a state, especially for top incomes. See Partridge et al. (1996); Morrill (2000); Frank (2014); Sommeiller and Price (2014) for existing work on subnational inequality in the U.S.

[4]Visit this page for the online GRID portal. See McKinney et al. (2022) for findings in the U.S.

[5]See MOVS and NEWS pages on the Census website.

Our approach has many strengths, but the measures constructed for IDDA have some limitations. These stem from the specific populations and types of income observed. To answer our questions of interest, we examine the universe of U.S. tax filers and W-2 recipients. These are certainly important groups, but they are not representative of all U.S. workers or households, and we did not attempt to re-weight the data to reflect other important populations of interest. Also, the income from which our statistics are tabulated is limited to pre-tax and pre-transfer sources. This means it is inadequate for studying questions in which income after redistribution is a key component—for example, questions related to poverty or consumption.

This paper proceeds as follows. We describe IDDA's construction in Section 2. In Section 3, we use IDDA to analyze trends in earnings inequality for detailed race and ethnicity groups, and we compare these to what might be inferred from the Current Population Survey (CPS). Section 4 describes patterns in income mobility and conditional income changes for the same groups in IDDA. In Section 5, we ask similar questions to those in previous sections, but we provide analysis for groups and places that are not readily available in any public sources: Native people living in Native areas. Section 6 concludes.

2 IDDA Construction

The Income Distributions and Dynamics in America (IDDA) dataset consists of novel granular statistics on the distribution of incomes, income changes, and income mobility. This dataset is generated from underlying microdata that combine select income and geographic information from the universe of individual tax returns with demographic information available from various sources through the U.S. Census Bureau. The key features of these data are difficult to collectively replicate in other settings: for detailed U.S. demographic groups and subnational geographies, they provide high-quality measurements of top incomes and income dynamics using statistically meaningful sample sizes and longitudinal linkage of individual observations.

A statistic $\mathcal{S}_{k,g}^{l,t}$ in IDDA is defined by four dimensions: k denotes the primary income source and income concept; t denotes the year; l denotes the geographical location, U.S. or state; and g denotes the demographic group. Time and geography are straightforward dimensions, but we discuss income types, estimation samples, and the available demographic groups in this section.[6]

2.1 Primary Data Sources

IDDA statistics are generated for select income concepts derived from the universe of individual tax returns. We report IDDA statistics from two primary data sources: (i) individual-level earnings data built from the universe of Wage and Tax Statements, or Form W-2s, and (ii) address-level household income data based on the universe of Income Tax Returns, or Form 1040s.

The requirement to file an individual federal income tax statement is subject to various exemptions, including a minimum gross income filing requirement. In contrast, the U.S. Internal Revenue Code (see U.S. Code, Title 26, section 6051) requires employers to file a W-2 for every employee. Therefore, the primary W-2 data source spans the universe of earnings from formal employment in the U.S.: from the highest values to the smallest earnings for individuals with limited labor force attachment.

However, labor force attachment can vary substantially across demographic groups or over the business cycle. In order to help make earnings statistics more comparable across demographic groups and years, we define a secondary individual earnings data source restricted to prime-age workers (PAW) only: individuals ages 25-54 with annual W-2 earnings above the equivalent of earning the federal minimum hourly wages for 20 weekly hours over 13 weeks. In the absence of sub-annual employment information, we use total earnings as a proxy for labor force attachment. The longitudinal dimension of the PAW individual data also allows us to measure how many workers enter or leave this notion of labor force attachment.

2.2 Income Concepts and Measures from Administrative Tax Data

Form W-2 earnings. The W-2 data we use covers tax years 2005 to 2019 and includes selected fields. IDDA contains measures for the following W-2 tax data categories: (i) individual wage and salary compensation, (ii) deferred compensation, and (iii) their sum. Wage and salary compensation is reported in Box 1 of Form W-2 and is positive for all earners included in our measurement datasets. Deferred compensation is one form of compensation recorded in Box 12 and may be positive or zero. While a worker's total compensation may include other components, such as

[6]More details can be found in the online documentation available on the Minneapolis Fed IDDA download page.

employer-sponsored health care, retirement contributions, or other benefits, we only observe these two components and treat their sum as a proxy for total compensation.

From tax units to households. Even though household-level income information is commonly available in surveys, tax forms do not readily provide a household unit construct: members of a household may file their tax returns jointly or separately. According to the Census Bureau, "A household consists of all the people who occupy a housing unit" (U.S. Census Bureau, 2024). Therefore, we aggregate Form 1040 incomes from tax filing units to address-level incomes as a measure of total "household" income available to each individual member.

To construct these household incomes, we use linkages to the Census Bureau Master Address File ID (MAFID) associated with the individual people listed as primary or secondary filers on each Form 1040. We circumvent issues associated with the notion of a "household head" or the assumptions required for the apportionment of household income among its members. We do so by aggregating income values across all Form 1040s sharing a common MAFID, and assign this total to each co-residing member. The result is a concept in which each individual in the data is attached to the total income resources at their "physical address household." While, because of double counting issues, this concept does not lend itself to distributional national accounts, it allows us to preserve the rich variety of individual demographic characteristics within a household: we are able to document top household incomes and to contrast these statistics by individual race/ethnicity, age, and related intersections. In Appendix B, we leverage individual-level linkages to the restricted-use CPS ASEC microdata and compare IDDA households with matched CPS households.[7]

Form 1040 household income concepts. The federal individual income tax statement data we use covers tax years 1998 to 2019 and includes a limited number of income fields. Specifically, IDDA contains measures for three Form 1040 income categories: (i) wage and salary income (WSI), (ii) adjusted gross income (AGI), and (iii) taxable non-wage income (NWI), their difference. Each income tax category is aggregated from tax-unit-level values into a household-level total income value using the MAFID as described above. While Form 1040 wage and salary income is zero

[7]See also Guvenen and Kaplan (2017) for a discussion on income measurement units in income tax data and differences between individuals, tax-filing units, and households when it comes to top income inequality.

or positive, AGI may be negative because non-wage income is not necessarily positive. Taxable non-wage income encompasses numerous types of income, including, as applicable, Schedule C self-employment profit or loss, interest and dividends income, capital gains or losses, and taxable retirement income, less deductions. Unfortunately, we are not able to observe all of these individual components separately. For a detailed description of the components of AGI, see Section 3 of the technical documentation.

2.3 Demographic Groups

Individual demographic characteristics, in our primary measurement data sources, use the assignment of the Census Bureau's unique, anonymized protected identification key (PIK) to all data files we use (Wagner and Layne, 2014). The PIK also facilitates longitudinal linkage, and we use the panel dimension of the data to document the distribution of income growth and mobility.[8] As in Akee et al. (2019), this allows us to link information on race, ethnicity, gender, age, foreign born status, and other demographic characteristics to individual tax records. Obtaining near-universal, high-quality administrative income data for minority racial and ethnic groups (and their intersections with gender or age) is an important feature.

Our main source for determining race and ethnicity is the Census Bureau's 2020 Best Race and Ethnicity Administrative Records Composite File, which supplements data collected via census or survey with data from a variety of sources—including records from the Department of Housing and Urban Development, the Temporary Assistance for Needy Families program, the Indian Health Service, and other agencies—to assign a single race and ethnicity (Hispanic or non-Hispanic) to individuals in the Census Bureau data system.

The large size of the IRS dataset and the quality of Census Bureau PIK/MAFID linkages allow us to disaggregate statistics for six major race and ethnicity groups: Hispanic, non-Hispanic Asian, non-Hispanic American Indian or Alaska Native (AIAN), non-Hispanic Black, non-Hispanic Native Hawaiian or other Pacific Islander (NHOPI), and non-Hispanic White. At the U.S. level, statistics are also reported for the "non-Hispanic other or multiple-race" group.[9] Sex, place of birth, and year

[8] As discussed below, we construct income dynamics statistics conditional on initial period income. This further divides potentially small demographic cells into both base-year income brackets and final-year income brackets.

[9] The non-Hispanic other or multiple race group makes up about 1.5 percent of the IDDA samples. This group is diverse, and the share of individuals identifying as multi-racial is growing. We leave a more complete measurement of incomes for multi-racial individuals for future research, since statistical guidelines and standards on reporting

of birth and death (which determine age) are drawn from Social Security Administration records. State of residence is taken from Form 1040 or any available information returns.

Individuals are excluded from the cross-sectional data if we are unable to link key demographic or geographic information or if tax records indicate conflicting tax unit information. We also exclude individuals whose MAFID is shared by an unusually large number of records.

Once sample selection and demographic linkages are made in the cross-sectional files, we link records longitudinally over one- and five-year time horizons. Demographic information and state of residence are taken from the initial year.

2.4 Overall Size and Composition

The Census Bureau's Person Identification Validation System (PVS) uses personally identifiable information (PII) (e.g., name, date of birth, etc.) to uniquely map social security numbers (SSNs) and individual taxpayer identification numbers (ITINs) into PIKs.[10] As a result, datasets that contain SSNs or ITINs, such as tax records, have very high PIK assignment rates (97 percent or higher). PIK assignment rates for files that do not contain this information (such as data from the decennial census and ACS, which do not collect it) are somewhat lower (90 to 93 percent) but still high in absolute terms (Mulrow et al., 2011). False assignment rates, however, are extremely low (Layne et al., 2014). The IDDA base datasets naturally inherit these high PIK match rates, as shown in the top panel of Table 1, for the year 2010. As a result, the primary datasets used for measuring IDDA income statistics are large, even for the minority race/ethnicity groups.

Table 1 also shows the demographic composition in 2010 in our primary IDDA data sources and in the CPS samples created using the IPUMS CPS dataset (see Flood et al., 2023). Overall, demographic shares are similar, even though the IDDA data derived from tax filings are not re-weighted to be representative of the overall population of filers and non-filers. The Form 1040 IDDA data source for household incomes has fewer 16-to-24-year-old individuals than the Form W-2 IDDA data source or the CPS data. This is not entirely surprising: in the Form 1040 household data source, we assign the address-level household income measure to the primary and secondary filers only. We also have fewer Hispanic, foreign-born, or non-Hispanic NHOPI shares in IDDA data

race/ethnicity in administrative data are actively changing. We do not report statistics for this group at the state level for this reason.

[10] See Wagner and Layne (2014) for more details.

sources, compared with shares in CPS samples. Non-Hispanic White and U.S.-born shares are higher in IDDA data sources than in the CPS.

Table 1: IDDA Sample Sizes and Composition (2010)

	Household-1040	Individual-W2	CPS Household	CPS Individual
In Numident	182,200,000	150,400,000	-	-
Has age, gender, and state	181,000,000	146,700,000		
Has race/ethnicity	178,000,000	144,300,000		
Has valid MAFID	169,300,000	-		
Final Sample N	169,300,000	144,300,000	153,586	95,094
Demographic Composition				
Female	52.1%	49.6%	51.7%	48.0%
Male	47.9%	50.5%	48.3%	52.0%
Hispanic	11.3%	12.9%	14.7%	14.8%
Non-Hispanic AIAN	0.7%	0.9%	0.7%	0.6%
Non-Hispanic Asian	4.6%	4.6%	5.1%	5.1%
Non-Hispanic Black	10.1%	12.0%	11.5%	10.8%
Non-Hispanic NHOPI	0.1%	0.2%	0.3%	0.3%
Non-Hispanic Other	1.3%	1.5%	1.3%	1.2%
Non-Hispanic White	71.8%	68.0%	66.5%	67.1%
Foreign born	13.9%	13.2%	15.5%	15.8%
Not Foreign born	86.1%	86.8%	84.5%	84.2%
16-24	8.8%	16.4%	16.1%	13.6%
25-34	18.5%	21.2%	16.9%	21.9%
35-44	18.7%	20.2%	16.6%	21.3%
45-54	20.9%	21.9%	18.3%	22.5%
55-64	17.3%	15.3%	15.6%	15.9%
65+	15.8%	5.0%	16.5%	4.8%

Note: IDDA is built from the universe of W-2 and 1040 income tax returns merged to demographic and geographic information via the PIK. Table 1 shows the total number of PIK-level records in this underlying dataset after successive sample restrictions, beginning with our initial merge to the Census Numident. N sizes and the sample demographic composition are reported for 2010, a year in the middle of our data series, along with the corresponding values in the CPS ASEC. We do not expect linkage to race/ethnicity information to change substantially in decennial census years, because of the prioritization of race/ethnicity data sources described above.
Source: IDDA and IPUMS CPS. Release authorization CBDRB-FY24-0131.

2.5 IDDA Modules and Availability of Granular Statistics

We use a variety of statistics to characterize income distributions within years, as well as conditional income changes and mobility across pairs of years. Table 2 lists these categories of statistics, which we term *modules*, as well as the demographic characteristics we use to define groups. We build on Akee et al. (2019) by constructing yearly state-level statistics on income inequality by race, by race and age, and by race and gender for different types of income. These measures include group-percentile income values, top income shares within demographic groups, and the share of top income held by members of different demographic groups. We also build on the contribution of McKinney et al. (2022) in the Global Repository of Income Dynamics (GRID) project by documenting percentiles of one-year income changes and five-year income changes by initial income level, by type of income, by demographic group, and across states. For a more extensive definition of the statistics included in each module of IDDA, refer to the technical documentation.

Table 2: Summary of statistics in IDDA

Statistics		Demographic characteristics defining groups
Income levels and income shares	Transition matrices and income change distributions	
Percentile values: p10, p25, p50, p75, p90, p95, p98, p99, p99.9, p99.99, etc., as sample size allows	**Transition matrices**: $P(B_{y+k} \mid B_y)$ for k={1,5} and income bins B={missing, p0-p24, p25-p49, p50-p74, and p75-p100, or p75-p89 and p90-p100}	**Race/ethnicity**: Hispanic, Non-Hispanic Black, Non-Hispanic AIAN, Non-Hispanic Asian, Non-Hispanic NHPI, Non-Hispanic White
Top income shares (within group): of all income earned by a given group, what share was earned by the top 10%, 5%, 2%, 1%, .1%, .01%, etc. of earners, as sample size allows		**Age**: 16-24, 25-34, 35-44, 45-54, 55-64, 65+
Top income shares (across groups): of income earned by the top 10%, 5%, 2%, 1%, .1%, .01%, etc. of all earners (as sample size allows), the share earned by members of a given group	**Conditional income changes**: mean, p10, p25, p50, p75, and p90 of nominal income changes for individuals starting in each income bin B between y and y+k	**Gender**: male, female
Top income population shares: The share of the top 10%, 5%, 2%, 1%, .1%, .01%, etc. of earners (as sample size allows) belonging to a given group		**Place of birth**: U.S.-born, foreign born

Note: p# indicates percentile value. Top income percentiles used for state-level inequality statistics go up to the 98th percentile. AIAN = American Indian or Alaska Native. NHOPI = Native Hawaiian or other Pacific Islander. Top income bins in transition matrices and conditional income changes are consolidated into a single p76-p100 bin for estimates at the state level. Estimates are produced nationally and at the state level within the groups listed for each demographic characteristic, as well as for two-way interactions of select demographic characteristics.

All statistics in IDDA are calculated within an income data source and income concept, a year, and a geography, and may be defined within or across demographic groups. The demographic groups included in the dataset vary across the different statistics modules and by sample and geography, in part to manage the population size underlying each statistic. While IDDA is constructed from large data, the granular information it provides can still lead to small samples, and some statistics are suppressed as a result.[11]

Table 3 and 4 summarize the availability of statistics in each of these three categories – income levels, transition matrices, and conditional income changes – by sample and geographic level. Table 5 provides a more detailed analysis of availability for individual race/ethnicity subgroups. Availability is simply the percentage of all defined statistics that are available (not suppressed) given the demographic disaggregations reported in a particular sample and geography. For individual race/ethnicity groups, availability is expressed as a percentage of all defined statistics pertaining to a specific subgroup, including intersections of age and race and of race and sex. For example, statistics defined for the groups Asian Male, Asian Female, and Asian 25-34 each count as 1 in the denominator of the availability rate for the non-Hispanic Asian group.

Table 3: Availability of Statistics by Demographic Group: Form 1040 data (1998–2019)

IDDA Module	Defined	All	Age	BPL	Race	AgeXRace
US Household-1040						
Income Levels	154,176	100	100	100	90.8	83.9
Income Changes	51,300	100	100	100	100	
Transition Matrix	59,850	100	100	100	100	
State Household-1040						
Income Levels	587,928	100	100	100	94.6	
Income Changes	1,395,360	100	100	100	94.9	
Transition Matrix	1,395,360	100	100	100	92.2	

Note: Columns provide the total number of defined statistics in each IDDA sample and geography, along with the corresponding availability rate in percentages. Each statistic is defined by a geography, sample and income concept, year(s), and demographic group. For example, the total number of transition matrix statistics defined at the state level includes all possible transitions between income quartiles, multiplied by 50 states, multiplied by the total number of income concepts, demographic groups, and pairs of years for which that statistic is computed. Availability rates for statistics that are not disaggregated by demographic group are reported in the "All" column. BPL represents place of birth (U.S. or foreign-born). Source: IDDA, per release authorization CBDRB-FY23-0277.

In general, availability is lower at the intersections of age and race, which are reported in the U.S. and state W-2 income levels, U.S. W-2 transition matrices and income change distributions, and U.S. 1040 income levels. Availability is quite high for cells defined over age, birthplace and sex groups. For race and ethnicity groups, coverage falls as more intersections are included and statistics are reported further into the tail of the income distribution. Statistics are most often suppressed for the Native Hawaiian or other Pacific Islander and American Indian or Alaska Native groups within individual U.S. states. Yet, it is rare that a group-state combination is excluded

[11] Note that each IDDA statistic is based on the universe of relevant tax records, not a randomly selected sample. It is unclear what commonly used measures of uncertainty like standard errors represent in this context. Thus, we have produced only point estimates for this analysis.

Table 4: Availability of Statistics by Demographic Group: Form W-2 Data (2005-2019)

IDDA Module	Defined	All	Age	BPL	Race	Sex	AgeXRace	AgeXSex	RaceXSex
US Individual-W2									
Income Levels	121,680	100	97	100	91.2	100	80.6	91.9	86.7
Income Changes	110,880	100	100	100	100	100	99.3	100	100
Transition Matrix	129,360	100	100	100	100	100	94.8	100	99.3
US PAW-W2									
Income Levels	80,370	100	99.5	100	90.5	100	85.1	94.6	84.8
Income Changes	72,000	100	100	100	100	100	100	100	100
Transition Matrix	120,816	100	100.0	100.0	99.9	100	95.4	100.0	98.7
State Individual-W2									
Income Levels	1,054,170	100	97.9	100	95.8	100	74.9	93.2	89.8
Income Changes	499,392	100	100	100	95.9	100			
Transition Matrix	499,392	100	98.8	99.6	86.2	100			

Note: Columns provide the total number of defined statistics in each IDDA sample and geography, along with the corresponding availability rate in percentages. Each statistic is defined by a geography, sample and income concept, year(s), and demographic group. For example, the total number of transition matrix statistics defined at the state level includes all possible transitions between income quartiles, multiplied by 50 states, multiplied by the total number of income concepts, demographic groups, and pairs of years for which that statistic is computed. Availability rates for statistics that are not disaggregated by demographic group are reported in the "All" column. BPL represents place of birth (U.S. or foreign-born). Source: IDDA, per release authorization CBDRB-FY23-0277.

from the IDDA data entirely, and as a result, the proportion of the U.S. working population that is not covered in IDDA is very small.[12] The fact that some suppression is still required emphasizes the importance of preserving population coverage of the tax data.

2.6 Limitations

Despite its universal underlying administrative data, IDDA income measures have important limitations. First, incomes used in IDDA are only pre-tax and taxable incomes from tax returns: IDDA incomes therefore do not reflect informal incomes or non-taxable incomes. Second, IDDA does not contain non-taxable public transfers, a very important income source for low income households in particular. In IDDA, statistics for lower earning individuals and households reflect income earned through formal employment or other non-wage taxable income sources. Researchers interested in

[12] For example, for 2010, percentiles of income from Form W-2 are not available for the Native Hawaiian or other Pacific Islander group in Delaware, Rhode Island, Vermont, or the District of Columbia. However, the population represented by these statistics was 0.38 percent of the total working NHOPI population. The combinations of race and age for which IDDA did not include any percentiles of income in 2010 accounted for only 0.015 percent of the total working U.S. population. Higher in the distribution, suppression is more common, but even here, the states where statistics are suppressed represent small fractions of the total population. The 98th percentile of income was suppressed for NHOPI earners in 21 states and AIAN earners in 2 states, but those states represented only 4.57 percent of the total working NHOPI population and 0.11 percent of the total working AIAN population, per ACS estimates.

Table 5: IDDA Availability by Race/Ethnicity

Module	Intersections	Hispanic	AIAN	Asian	Black	NHOPI	White
US-Level							
Household-1040							
Income Levels	age	91.7	76.4	89.4	88.4	68.9	95.4
Income Changes	-	100	100	100	100	100	100
Transition Matrix	-	100	100	100	100	100	100
Individual-W2							
Income Levels	age, sex	89.9	74.1	87.7	90.6	66.4	92.3
Income Changes	age, sex	100	99.6	100	100	97.5	100
Transition Matrix	age, sex	100	95.0	99.9	100	83.5	100
PAW-W2							
Income Levels	age, sex	93.8	77.0	90.5	93.2	70.9	94.0
Income Changes	age, sex	100	100	100	100	100	100
Transition Matrix	age, sex	100	96.2	100	99.6	87.4	100
State-Level							
Household-1040							
Income Levels	-	99.9	96.8	99.9	98.2	72.5	100
Income Changes	-	100	97.1	99.9	98.8	73.5	100
Transition Matrix	-	99.8	95.1	98.9	97.7	61.8	100
Individual-W2							
Income Levels	age, sex	91.3	76.5	88.8	87.8	44.0	95.0
Income Changes	-	100	98.2	100	99.9	77.5	100
Transition Matrix	-	97.5	83.6	94.5	94.4	47.1	100

Source: IDDA.
Note: Table 5 reports availability rates for individual race/ethnicity groups in IDDA. The column "intersections" indicates whether statistics in the geography and sample are provided for the intersection of age and race, race and sex, or neither. In general, statistics are provided further into the tail of the income distribution of the U.S.-level data than that of the state-level data. Income levels are reported up to the 98th percentile at the state level and 99.999th percentile nationally. Transition matrices and conditional income changes are calculated within quartiles of the state-level income distributions. At the U.S. level, the top income quartile is divided into two smaller brackets (the 75th-90th percentile and above the 90th percentile). Release authorization CBDRB-FY23-0277.

studying poverty or income available for consumption are encouraged to use statistics from a more comprehensive source.[13] Third, IDDA does not have a breakdown of non-wage incomes by type. Given the large variety of taxable non-wage incomes and the accounting rules involved, caution should be exercised when interpreting non-wage income statistics. Fourth, IDDA is representative only of filed incomes and the population of filers, not all incomes.[14] Finally, IDDA statistics are not available for all feasible demographic groups or places, and IDDA does not contain any statistics on wealth.[15]

3 Income Inequality Trends For Aggregate and Granular Populations

3.1 Changes in Aggregate Distributional Statistics

In order to put in context the patterns of income inequality for race and ethnicity that IDDA reveals, we first plot changes in household adjusted gross income, by percentile, over time for the population of U.S. tax filers as a whole. This provides a baseline about patterns for U.S. earners and also allows comparisons to statistics calculated from public sources.

To begin, Figure 1 graphs the log difference (or approximate percent change) in percentile values for real household income relative to their values in 1998. Panel (a) plots household income growth using IDDA. In Panel (b) of Figure 1, we produce the same cumulative changes in real log household incomes using publicly available data from the Annual Social and Economic Supplement (ASEC) to the CPS; hereafter, we refer to this simply as the CPS. We use income concepts reported in IPUMS CPS that align as closely as possible with the concepts measured in our administrative data (Flood et al. 2023). For W-2 earnings, the CPS reports a close analog. For household AGI from household 1040 filings, the closest CPS income concept does not align as well.[16] We compute statistics in the public-use CPS microdata analogous to those we analyze in IDDA, imposing only

[13] These issues are discussed in detail in Corinth et al. (2022), among others, and data on the full set of income available for consumption is provided in the Comprehensive Income Dataset, `https://cid.harris.uchicago.edu/`.

[14] Evidence suggests that around 90 percent of those who are required to file in our period actually do so (Erard et al., 2020). We have found no evidence on whether voluntary filing is a persistent trait, but Erard et al. (2020) report a voluntary filing rate with only modest fluctuations over the three-year period they examine.

[15] A key limitation of IDDA is that certain characteristics, including education and occupation, are not visible from tax data. We produce averages by demographic group for certain ACS characteristics in Table A.1 in the Appendix.

[16] Specifically, the corresponding variables in the CPS are HTOTVAL for household AGI and WSAL_VAL for W-2 earnings. There are several differences between the types of income included in HTOTVAL and household AGI. AGI includes capital gains and excludes non-taxable transfers. HTOTVAL excludes the former and includes the latter.

the restriction that CPS state-group cells must contain at least 50 observations in order for us to include a CPS-derived statistic in our analysis.[17]

Figure 1 produces a familiar pattern, and at the most general level, the two sources tell a similar story: income inequality widened since the late 1990s, though more modestly than in earlier decades, with recessions slowing income growth more sharply (or even eroding income) for the lowest earners. Both series also show that income growth in recoveries has been slow to return lower earners to pre-recession levels.

However, the details suggest material differences in the patterns of income growth identified in the two sources, even at this highly aggregate level. These are most substantial at higher percentiles. Panel (a) in Figure 1 shows that the 90th percentile of household AGI in IDDA had risen 30 percent relative to its 1998 level by 2018, while the 25th percentile of household AGI increased by less than half that, and the 10th percentile of household AGI had not grown at all. Panel (b) shows that the CPS produces patterns that suggest it may be an unreliable measure for the highest percentiles. In the highest household income bin shown (the 98th percentile), the CPS series fluctuates widely and indicates shallower income growth for the highest percentiles. Large volatility in these top income series could reflect actual earnings changes, but they are likely also be related to changes in how the public CPS preserves confidentiality at top incomes as well as to non-random misreporting of high incomes, as is consistent with findings in Bollinger et al. (2019).[18]

The IDDA series also suggest that changes in household income percentiles among 1040 filers unfolded relatively smoothly year to year, with some notable exceptions. The sharp temporary changes at low income percentiles in 2007 were likely due to filing changes driven by requirements for receipt of stimulus checks.[19] Sharp changes in the value of household income at the highest percentiles – the 98th percentile, for example – also occur in the IDDA series, but these large

[17] This is a much lower standard than that applied to IDDA statistics. For any given IDDA statistic to be reported, we require a minimum of 30 contributing observations; this threshold applies to the numerator if the statistic is a share. The CPS 50-observation threshold applies at the state-group level, not the statistic level. For shares in the CPS, we apply a higher threshold of 250 observations at the state-group level, in order to have sufficient observations in the numerator.

[18] We discuss the impact of definitional differences and misreporting of income to the CPS patterns as compared with IDDA in detail in Appendix B.

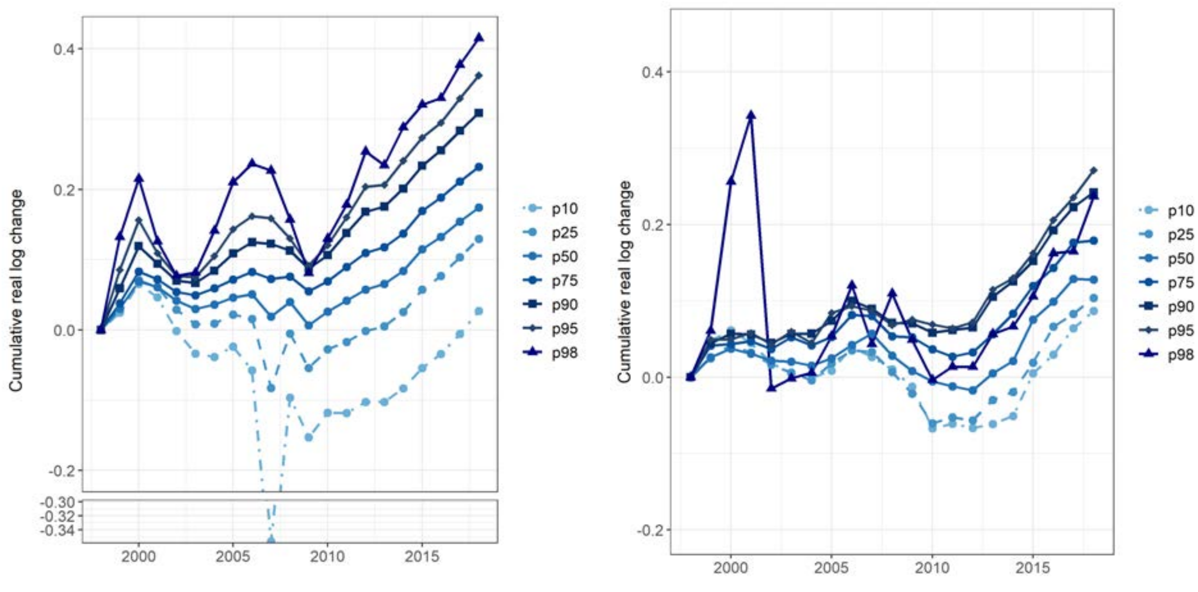
[19] A similar spike appears in 2019. In both 2007 and 2019, the data show an excess of $0 returns, consistent with temporary changes in filing related to stimulus collection (Internal Revenue Service, 2009). This mechanically shifts down the household income percentile values, especially at the bottom of the distribution. We use 2018 as the endpoint in our analysis for this reason. The CPS also suffers from continuity issues in 2019, related to difficulties in administering the ASEC in March 2020 (IPUMS, 2020).

procyclical fluctuations are probably not due to extensive margin changes in filing behavior. We use the long time series in IDDA to "look through" the filing-related fluctuations at the lowest percentiles, and we interpret fluctuations at the highest percentiles as real.

Figure 2 repeats the same exercise as in Figure 1 for individual earnings from 2005 onwards. Panel (a) plots cumulative log changes in real individual W-2 earnings using IDDA. As was the case before, Panel (b) is based on the public-use CPS ASEC microdata. At a high level, the two sources again tell broadly similar stories. Both also show that the final years of recovery from the Great Recession saw greater growth in wage earnings for the lowest earners, even though this did not translate to greater income growth for the lowest-earning households.

But again, even at this aggregate level, the individual earnings series in Figure 2 show meaningful differences across sources. First, for the lowest wage earners (at the 10th and 25th percentiles), IDDA indicates trend earnings growth beginning at the trough of the Great Recession. This growth persists through the end of the data period, albeit from a low level. By contrast, in the CPS, relative earnings growth for the lower percentiles is not clearly apparent until later in the recovery. For the highest wage earners, IDDA shows earnings were flat or modestly declined after the Great Recession, before resuming greater relative growth at higher percentiles. The CPS instead suggests that the highest earners saw some of the greatest earnings declines in the Great Recession and recovered no faster than most other groups.

These differences combine to imply some material differences between the evolution of inequality in the IDDA series as compared to the CPS. These are summarized in Figures A.1 and A.2, which plot several key percentile earnings ratios. Ratios from both IDDA earnings series align well with CPS ratios for the center of the distribution, p75:p25. These ratios are flat in both data sources, for both households and individuals. Differences arise when comparing the highest and lowest deciles (p90:p10) in both sources or the highest household incomes with the median (p98p50). Broadly, these show more ongoing changes in inequality over the 2010s than are apparent in the CPS. In the IDDA series, individual W-2 earnings show a marked decline in inequality between the highest (p90) and lowest earners (p10) from 2010 to 2019. This decline begins earlier than in the CPS, and is larger in absolute terms, but the final level of inequality is considerably higher in IDDA. In the household statistics, IDDA shows that the extremes of the distribution became steadily more unequal, as the p90p10 and p98p50 ratios both widened. The CPS shows at most a modest change in the analogous measures. These differences suggest potentially new insights into the evolution of U.S. inequality since the late 1990s. However, our aim in this paper is to assess IDDA as a source for patterns in earnings inequality for detailed subnational groups, so we leave these questions for future work.



(a) IDDA household income growth

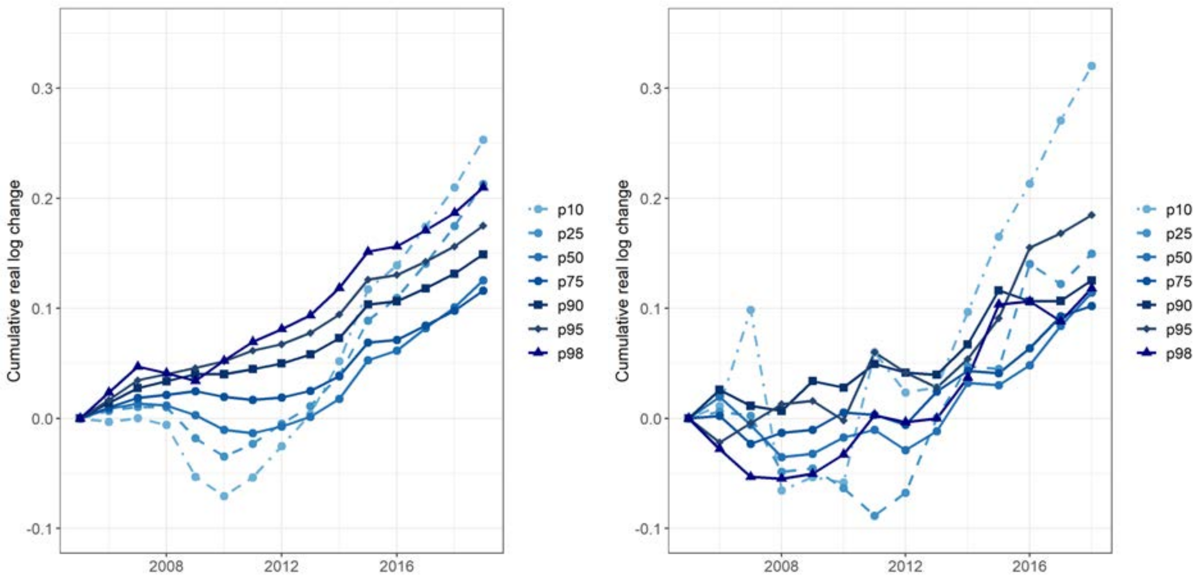
(b) CPS household income growth

Figure 1: Household income growth in IDDA vs. CPS

Source: IDDA and IPUMS CPS.
Note: CPS statistics calculated by the authors following IDDA documentation and using the sample of all ASEC respondents aged 16-plus. Data period for both sources is 1998 to 2018. Release authorization CBDRB-FY23-0277.

3.2 Changes in Granular Distributions

While examining the major earnings inequality patterns at the national level provides a helpful baseline, IDDA is designed to study these patterns in much smaller populations. How does IDDA compare with the CPS when we study changes in earnings distributions for smaller groups? We examine groups at two subnational levels: the state level and the state-by-race and ethnicity level. We compare subnational IDDA statistics with analogous measures constructed using the CPS by running a series of cross-state regressions of the state-level change in a distributional statistic as calculated using the CPS on the change in the same statistic in IDDA. (Changes in the CPS are likely measured with more noise, so regressing changes in CPS measures on changes in IDDA measures reduces attenuation bias.) This is subject to the constraint that we require a CPS subnational



(a) IDDA earnings growth

(b) CPS earnings growth

Figure 2: Earnings growth in IDDA vs. CPS

Source: IDDA and IPUMS CPS.
Note: CPS statistics calculated by the authors following IDDA documentation and using the sample of ASEC respondents aged 16-plus who reported positive wage income. Data period for both sources is 2005 to 2018. Release authorization CBDRB-FY23-0277.

population to have at least 50 observations in order to compute distributional statistics for it.

The results using Form 1040 household income are presented in Table 6. In column (1), we report the number of states or state-by-race and state-by-ethnicity cells for which the CPS contains sufficient observations to compute within-state distributional statistics used to produce the table. In columns (2)–(6), we report, for a given income percentile, the results from regressing the change log income at that percentile over 1998 to 2018 in the CPS on the same change using IDDA. Each row in Table 6 corresponds to either state filers as a whole or to state-level race and ethnicity groups. Income percentiles are computed state-by-state for each group. Hence, each cell in the table is a coefficient on the IDDA statistic as a predictor of the CPS statistic from a separate univariate regression, with the standard error reported in parentheses. For example, the value 0.628 in column (2) in the top row is the coefficient from a state-level regression of the change in the log of 10th-percentile household income in the CPS on the change in log p10 household income in IDDA, over the 1998 to 2018 period. It indicates that the log household income 10th percentile in the CPS increased by about two-thirds as much as the one in IDDA, on average across states.

If the corresponding state-level CPS statistics were closely related to those in IDDA, coefficients would typically be near one, with narrow standard errors. The final two columns (7 and 8) report results from the same exercise, using changes in income percentile ratios instead of changes in log incomes.

Several points are clear from the Table 6. First, sample size limitations in the CPS prevent this analysis in many cases. As shown in column (1), the exercise is possible for fewer than half the states for three race and ethnicity groups: American Indian or Alaska Native, Asian, and Native Hawaiian or other Pacific Islander. For the last of these, data are insufficient to report any results from this comparison. Second, the standard errors indicate that – for many populations – statistics as computed in the CPS bear little relationship to those in IDDA; these noisier IDDA-CPS correlations are particularly prevalent at lower household income percentiles (see p10 and p25 in columns 2 and 3) and for smaller groups.[20]

A final point is that typically, coefficient estimates of percentile-level income growth are often far from one. In Table 6, these are often less than one; this finding is potentially related to concept differences across the sources. This means that on average, changes in household income in the CPS are smaller than the corresponding IDDA estimate at all percentiles across states, as shown in the first row of Table 6, which reports results for state-level income distributions that pool all race and ethnicity groups. In columns (2) through (6), all estimates are less than one.

Estimates in columns (7) and (8) show that the result of these percentile-by-percentile differences is different changes in earnings inequality by the end of the period. The cross-state estimates for long changes in income percentile ratios shown are both smaller than one. In fact, for the p98-to-p50 household income ratio in column (8), the estimated coefficient is only 0.214, with a standard error of 0.148. This illustrates a final takeaway from the table: state-level changes in inequality produced by the CPS are nearly unrelated to those measured in IDDA, particularly when comparing the highest to the more central percentiles, as in column (8).

Subsequent rows present the same analysis for state-level populations defined by race and ethnicity. As already noted, this exercise is not possible using the CPS for the AIAN and NHOPI groups, owing to small samples. In general, the conclusions of this exercise for state filers as a whole are apparent when state populations are defined by race and ethnicity.

[20] Results from a sample trimmed of outliers are similar and available upon request.

White filers, shown in the bottom row, are the only group for which distributional statistics can be calculated for all states in the CPS. For White filers, in column (2), we see that changes in the 10th percentile of household income in IDDA and the CPS align fairly well ($\beta = 0.98$). However, above the 10th percentile, the point estimates are farther away from one, as shown in columns (3)–(6). As a result, the CPS indicates smaller increases in within-group inequality among White households than those in IDDA.

The pattern is similar for Asian filers except for the lowest income percentile, although the CPS statistics can be calculated for fewer than half of U.S. states for this group, and the standard errors are larger. For Black and Hispanic filers, the picture is different. At the 10th percentile, the standard errors are so large that there is no statistically reliable relationship between the CPS and IDDA income changes, even though the CPS permits distributional estimates for more than half of states for these groups. In fact, the point estimate is negative for Hispanic income changes in the CPS relative to those in IDDA. Above the 10th percentile, IDDA and the CPS yield statistically similar estimates of changes in income percentiles for Black filers, and these estimates are close to one. In the final two columns, point estimates show that the CPS tends to indicate smaller increases in inequality (except for Black filers), but the standard errors show that this relationship is extremely noisy. This implies that for most states, the CPS and IDDA will give different readings on changes in inequality within groups defined by race and ethnicity.

In Table 7, we perform the same analysis, but this time on statistics calculated from W-2 earnings. Here, the income concepts align well, so evidence of under- or overestimating changes in earnings by percentiles – that is, coefficients unequal to one – is more likely to be driven by reporting differences than concept differences. Nevertheless, most of the major patterns in Table 6 are also apparent in Table 7. Cell sizes in the CPS remain an issue, naturally. In other words, state-level distributional statistics either cannot be computed at all for most states (as is the case for NHOPI, AIAN, and for p98 earnings) or that the relationship between CPS-derived statistics and those from the universe of W-2 recipients in IDDA is essentially noise.

Although the coefficients are generally better centered on one, standard errors remain relatively large. Consequently, on average, percentile by percentile earnings growth across states in the CPS is not closely aligned with that in IDDA, even for state earners as a whole, as shown in the top row. As was the case with AGI, the CPS indicates smaller increases in the 90th earnings percentile than those in IDDA (see column (6)). However, differences between IDDA and the CPS reverse at lower earnings levels. Results for all race and ethnicity groups combined show that 10th-percentile earnings increased more in the CPS than in IDDA. If we look to the right, estimates show this is true for percentiles up to the median as well. The bottom rows of the table show that this pattern holds for the group of individual White earners as well.

The final two columns in Table 7 show how changes in inequality measures in the CPS compare to IDDA when using the W-2 measures. When using the 1040 household income measures, the CPS tended to indicate smaller increases in inequality than IDDA. By contrast, in columns (7) and (8), we see that the inequality measures using W-2s show a less stable relationship between IDDA and the CPS. The CPS shows much larger declines in p90-to-p25 inequality than IDDA for all groups (top row) but not for White earners (bottom row). However, for the p98-to-p50 ratio, results in column (8) for the state populations as a whole show much smaller and largely noisy increases in this measure of inequality in the CPS than in IDDA. We also observe smaller and largely noisy increases in the p98-to-p50 ratio in the CPS, compared with IDDA, for White earners and Black earners. But for Hispanic W-2 earners, this relationship reverses, with the CPS indicating larger increases in inequality (though with large standard errors).

We conclude from this analysis that the CPS is problematic for calculating distributional statistics not only at the subnational level but also, in some important cases, at the U.S. level.[21] As is consistent with other work, we find that the CPS systematically underestimates incomes in the top percentiles and that it also diverges from administrative data at the lowest percentiles (Bollinger et al., 2019; Meyer and Mittag, 2019; Bee et al., 2023). Percentiles above the 90th are not well observed in the CPS, and we view our analysis as evidence that CPS-derived statistics for race ethnicity groups at the state level are largely noise due to sample size. Moreover, IDDA is the only feasible source for subnational income distributions for AIAN and NHOPI populations.

[21] We repeat the analysis in Table 6 and replace the CPS with the ACS for the purposes of constructing comparison statistics with a public source. The results appear in Appendix Table A.2. The relationship between IDDA and ACS-based statistics is closer than the one between it and CPS statistics; coefficients in the cross-state regressions are closer to 1 and more often significant. But in many cases, standard errors remain large and the ACS statistics are on average 10 or more percentage points larger or smaller than those in IDDA.

Table 6: Changes in State-level Distributional Statistics: CPS total household income vs. IDDA household AGI (1998-2018)

Estimated slope $\Delta(y)^{state}_{CPS} = \beta\Delta(y)^{state}_{IDDA} + \varepsilon^{state}$

Group	(1) N	(2) log(p10)	(3) log(p25)	(4) log(p50)	(5) log(p75)	(6) log(p90)	(7) p90p25	(8) p98p50
All	51	0.628	0.780	0.806	0.780	0.710	0.634	0.214
		(0.154)	(0.066)	(0.044)	(0.032)	(0.0361)	(0.087)	(0.148)
Hispanic	33	-0.511	1.060	0.820	0.755	0.793	-0.078	-0.381
		(1.330)	(0.159)	(0.097)	(0.101)	(0.092)	(0.479)	(0.784)
AIAN	7	1.230	0.400	0.447	0.624	0.675	2.330	
		(0.725)	(0.402)	(0.165)	(0.183)	(0.416)	(2.210)	
Asian	24	1.940	0.820	0.884	0.795	0.654	0.642	-0.475
		(0.893)	(0.259)	(0.163)	(0.120)	(0.126)	(0.328)	(0.550)
Black	30	0.624	1.200	1.100	1.030	0.932	1.320	0.078
		(0.506)	(0.336)	(0.251)	(0.205)	(0.127)	(0.603)	(0.652)
NHOPI	2							
White	51	0.977	0.853	0.765	0.771	0.708	0.752	0.178
		(0.173)	(0.075)	(0.0493)	(0.040)	(0.043)	(0.134)	(0.257)

Source: IDDA and authors' calculation using IPUMS CPS.
Note: Changes are computed from 1998 to 2018 for the household-level data, with the exception of Asian and NHOPI filers, for whom CPS data is available beginning in 2002. We choose not to compare 2019, the final year in the IDDA dataset, because of changes in tax filing and an unusually low CPS response rate that resulted from the Covid-19 pandemic. We compute the 10th-90th percentiles of income for subnational populations with at least 50 observations in the CPS. We compute the 98th percentile for subnational populations with at least 250 observations in the CPS. Release authorization CBDRB-FY23-0277.

3.3 Changes in Relative Earnings by Race and Ethnicity: Broadening Bayer and Charles (2018)

With over 6 million statistics, IDDA offers many possible ways for researchers to investigate earnings gaps by race and ethnicity. To demonstrate just one option, we use IDDA to replicate and extend some of the analysis in Bayer and Charles (2018)—hereafter BC—a paper that represents the current frontier of our understanding of the evolution of earnings gaps between Black and White men. The prime-age subsample of W-2 recipients in IDDA is similar to those from the BC sample of prime-age workers from the decennial Census and the American Community Survey (ACS).[22] We use this to extend the motivating analysis in BC.

In Figure 3, we plot estimates of the gap in earnings for Black and White men, following

[22]A comparison of demographic characteristics across the prime-age subsample of W-2 recipients in IDDA and prime-age workers in the CPS is provided in Appendix Table A.4.

Table 7: Changes in State-level Distributional Statistics: CPS individual wage/salary income vs. IDDA W-2 earnings (2005-2018)

Estimated slope $\Delta(y)^{state}_{CPS} = \beta\Delta(y)^{state}_{IDDA} + \varepsilon^{state}$

Group	(1) N	(2) log(p10)	(3) log(p25)	(4) log(p50)	(5) log(p75)	(6) log(p90)	(7) p90p25	(8) p98p50
All	51	1.510	1.120	1.110	1.050	0.912	0.817	0.441
		(0.116)	(0.067)	(0.068)	(0.065)	(0.061)	(0.137)	(0.418)
Hispanic	40	0.971	0.847	1.250	1.290	0.898	-0.051	1.340
		(0.258)	(0.172)	(0.141)	(0.174)	(0.204)	(0.261)	(0.854)
AIAN	4	1.060	1.260	1.250	1.090	0.844	1.250	
		(0.475)	(0.659)	(0.290)	(0.251)	(0.400)	(1.080)	
Asian	19	1.260	0.647	0.908	0.589	0.571	-0.113	
		(0.395)	(0.196)	(0.188)	(0.086)	(0.130)	(0.487)	
Black	32	1.210	0.876	1.140	0.981	1.040	0.311	0.279
		(0.187)	(0.121)	(0.203)	(0.331)	(0.232)	(0.110)	(0.309)
NHOPI	1							
White	51	1.580	1.220	1.120	1.060	0.950	1.140	0.173
		(0.128)	(0.063)	(0.062)	(0.076)	(0.074)	(0.151)	(0.438)

Source: IDDA and authors' calculation using IPUMS CPS.
Note: Changes are computed from 2005 to 2018 for individual earnings. We choose not to compare 2019, the final year in the IDDA dataset, because of changes in tax filing and an unusually low CPS response rate that resulted from the Covid-19 pandemic. We compute the 10th-90th percentiles of income for subnational populations with at least 50 observations in the CPS. We compute the 98th percentile for subnational populations with at least 250 observations in the CPS. Release authorization CBDRB-FY23-0277.

Bayer and Charles (2018), expressed as differences in the log of earnings at the median and the 90th percentile of the respective distributions. Dashed lines indicate the BC estimates.[23] Solid lines indicate estimates of the same earnings gaps from IDDA. The figure shows that to a first approximation, earnings gaps at the median and p90 in IDDA are similar to those estimated by BC, although gaps in IDDA are somewhat larger in all years where both measures are observed. Both series also show a modestly larger earnings gap at the 90th percentile than at the median.

The differences between the series grow after 2010, a period for which BC has only a single estimate. In the IDDA series, the gap at the median begins to widen. The gap at p90 also widens in the IDDA series, but in the BC series, it moves sideways. Overall, there is more divergence between the two series by 2014, when the BC analysis ends. The IDDA series shows that the

[23] The BC analysis uses decadal observations from the decennial Census starting in 1940, and concludes with the first set of three-year ACS estimates post-2010. The prime-age worker subsample in IDDA overlaps with the final portion of the BC period, and the earnings concepts (wage and salary) align well.

earnings gap at the 90th percentile for Black men relative to White men continued to expand through the end of the series in 2019, while the gap at the median stabilized at its wider, post-2015 level.

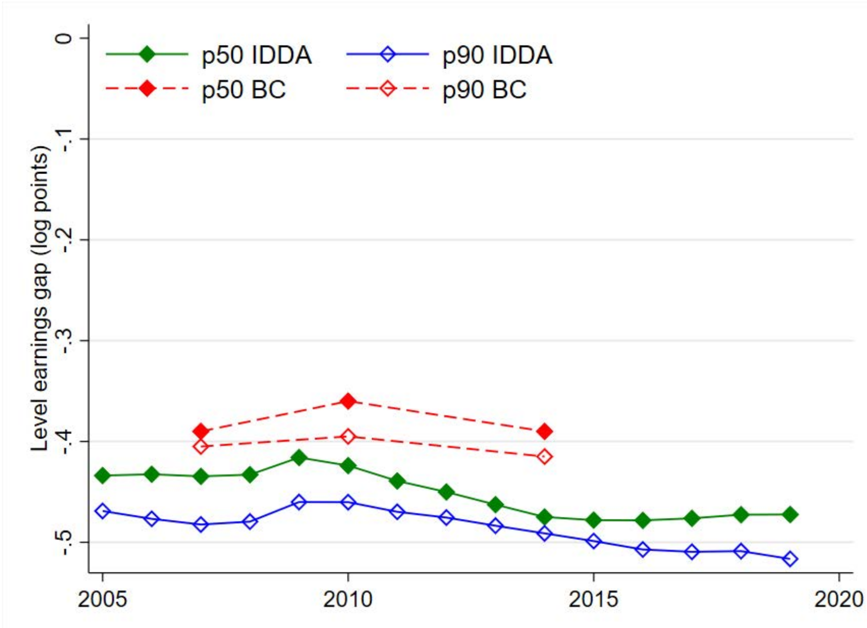


Figure 3: Log earnings gaps between Black and White male earners

Source: IDDA, Bayer and Charles (2018), authors' calculations.
Note: Figure charts the earnings gap between prime-age White and Black men at the median and 90th percentile using different data sources. Gap is measured in log points. Trends in red are reproduced from Bayer and Charles (2018) Figure IV using replication files. The IDDA prime-age sample includes workers aged 25-54 with earnings at least equivalent to working 20 hours a week for 13 weeks at the federal minimum wage. Ethnicity is non-Hispanic unless otherwise specified. Release authorization CBDRB-FY23-0277.

The detail in IDDA allows us to expand the BC analysis along several dimensions. We first ask whether the patterns in the median and p90 earnings gaps extend to earnings gaps higher in the distribution, which are difficult to calculate credibly in the ACS. Panel (a) of Figure 4 shows the results from plotting the Black-White earnings gaps for men at p98, in addition to the median and p90. The figure shows that moving into the tail results in substantial changes to the earnings gap. The earnings gap at p98 is almost double the gap at the median. Appendix Figure A.4a shows that the gap is even larger at p99 and p99.9. However, for the very highest partial percentiles, the gap narrows again, falling back closer to the gap at the median. Gaps at most percentiles also widen over time following the Great Recession. This is true for gaps at the median through p99.9. At the very highest sub-percentile, p99.999, the gap narrows more or less consistently over the period, shrinking from about 0.6 to less than 0.2 log points.

IDDA also allows investigation of earnings gaps at the state level.[24] Figure A.3a in the appendix shows the earnings gap at the median from Figure 3 as a bold line along with the same gaps for all states as lighter lines. The figure shows that gaps at the median follow similar trajectories across states, but the size of the gap varies considerably, ranging from about 0.2 to 1.2 log points at the end of the period. Rinz and Voorheis (2023) report that cross-state differences in Black-White earnings disparities overall are driven largely by variation in White earnings. Data from their paper are available and can form a useful complement to IDDA in exploring these questions at the state level.[25]

Using IDDA, we can also readily extend the BC earnings gaps to other race and ethnicity groups. Deriving statistics from the universe of tax forms allows for credible estimates of distributional moments even for populations that are small relative to the U.S. as a whole (AIAN and NHOPI earners) and those that are small in a large number of states (Asian, Hispanic, and even Black earners). We show BC-style analyses of median and p90 earnings gaps, as well as the p98 gap, for men in these groups in panel (b) of Figure 4. The figure shows that, relative to those for White men over the period since 2005, earnings at all three of these percentiles have grown for all other race and ethnicity groups, in contrast to relative earnings for Black men. This is true for groups where relative earnings in 2005 were below those of White men at the same percentile (AIAN, NHOPI and Hispanic) and for Asian men, who had relative earnings in 2005 that were roughly on par with those for White men.

The divergence since the Great Recession of Black men's earnings paths from those of men in other groups identified as non-White is striking. To understand if this experience is unique to Black men, we repeat the analysis in panel (a) for Black women, reporting their earnings gaps relative to White men in panel (c). Earnings gaps for Black women at the beginning of the period were larger than for men: a little under 0.6 log points at the median, versus a little over 0.4 for men. As was the case for Black men, earnings gaps for Black women increase considerably at higher percentiles. These gaps narrowed modestly before the Great Recession, but widened again after it at most percentiles. Figure A.4 in the Appendix shows that at the highest sub-percentiles, p99.9

[24] BC provide analysis at the region level.

[25] Broadly, the data from Rinz and Voorheis (2023) contain more distributional detail but less demographic detail and do not address person-level income changes over time.

through p99.999, earnings gaps with White men narrowed somewhat over the period.[26]

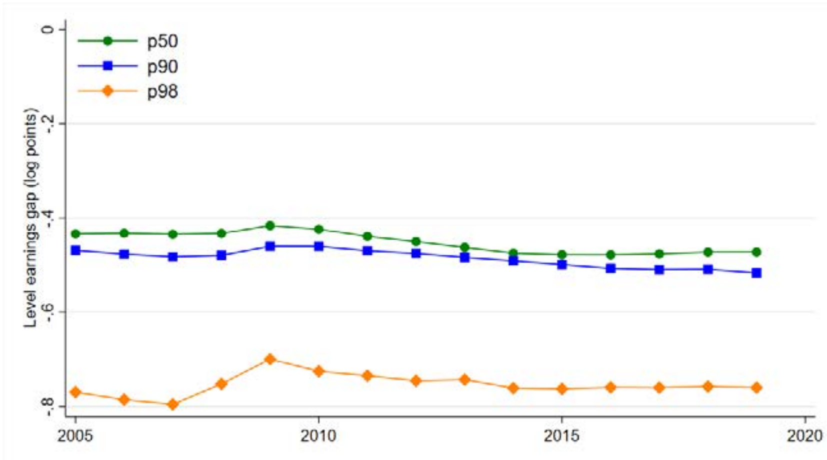
Earnings gaps with White men for women in other race and ethnic groups are shown in panel (d) for the same three percentiles reported for men. Hispanic women and Asian women experienced earnings gains relative to White men over the period. For Hispanic women, these gains came after 2015, and a large gap remains. For Asian women, earnings gains were steady over the period and have largely closed the earnings gap with White men at all three percentiles shown. NHOPI and AIAN women saw their earnings at these percentiles make modest gains relative to White men or hold steady.

We conclude that Black earners in the U.S. have experienced less earnings growth than earners from any other race and ethnicity group, relative to a comparison group of White men since the Great Recession. Black men are unique relative to other groups of men in seeing their earnings at all but the highest sub-percentiles decline relative to White men. Black women, too, saw some decline relative to White men. AIAN women and NHOPI women saw their relative earnings stagnate, but other groups of women (Hispanic and Asian) experienced earnings growth in the top half of the distribution, relative to White men. The unique divergence among Black men was undetected in BC, in part because of their data period but also because of limited ability to explore the relative experiences of other non-White earners and earners in higher percentiles.[27]

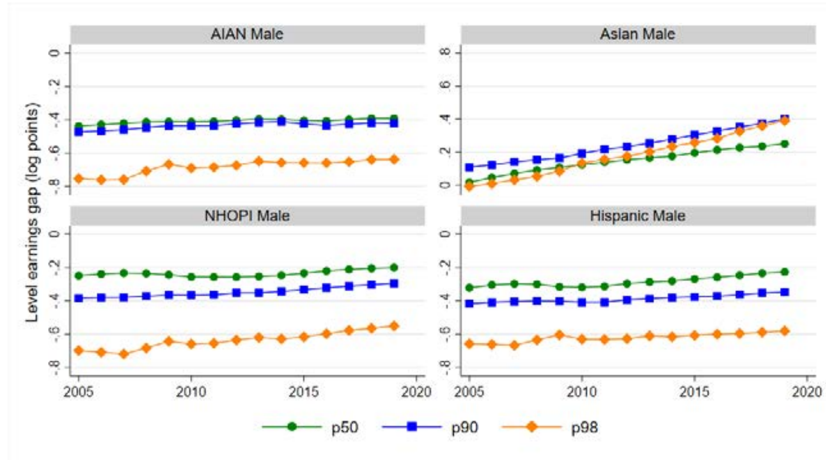
[26] Figures A.5 and A.6 in the appendix show that using White women as a reference group does not alter our conclusion that Black women's relative earnings declined while those of other women increased or held steady.

[27] A challenge with IDDA, like any aggregate statistic, is accounting for differences in characteristics that may contribute to the gaps in aggregate measures. For example, is the group of Black men in the U.S. changing over time in a way that would reduce their earnings relative to all other groups? Perhaps the group as a whole is becoming younger or less likely to be born in the U.S. IDDA statistics cannot be re-estimated holding population characteristics constant, but researchers can use other sources to control for or test hypotheses about changing observables in the aggregate. This is left for future research.

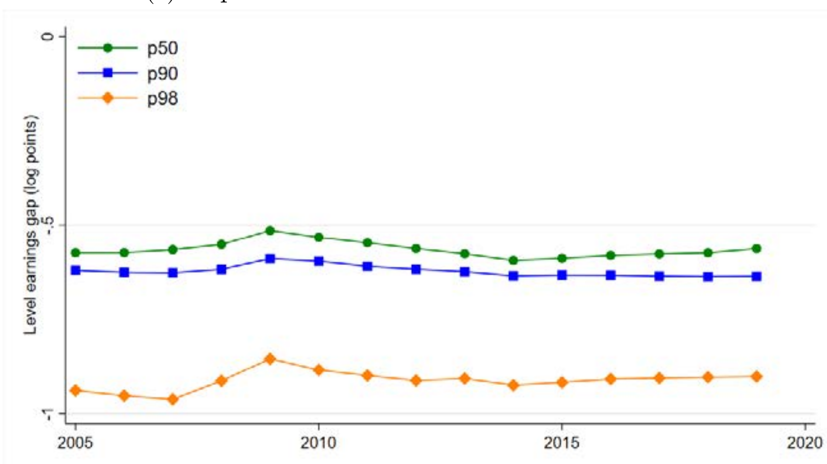
(a) Gap between Black men and White men



(b) Gap between non-White men and White men



(c) Gap between Black women and White men



(d) Gap between non-White women and White men

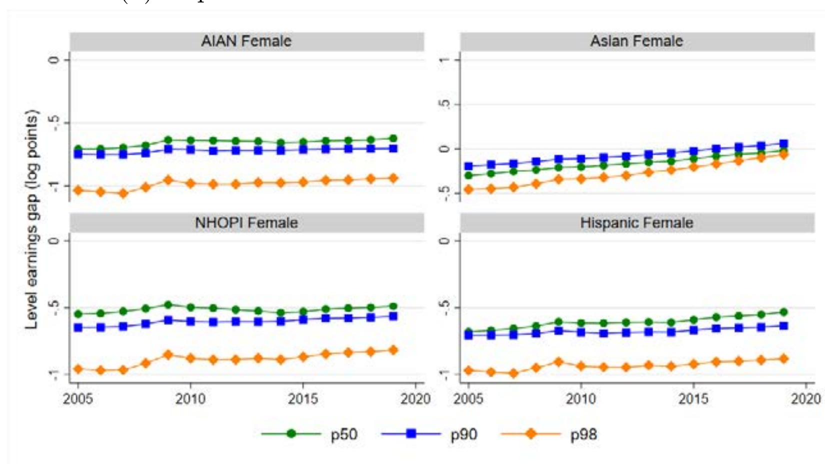


Figure 4: Log earnings gaps between non-White and White earners

Source: IDDA and authors' calculations.
Note: Each panel plots the earnings gap between prime-age non-White earners and White men, in log points. Panels (a) and (c) show earnings gaps for Black men and women across several percentiles; (b) and (d) show earnings gaps at selected percentiles for other non-White groups. Includes workers aged 25-54 with earnings at least equivalent to working 20 hours a week for 13 weeks at the federal minimum wage. AIAN abbreviates American Indian or Alaska Native. NHOPI abbreviates Native Hawaiian or other Pacific Islander. Ethnicity is non-Hispanic unless otherwise specified. Release authorization CBDRB-FY23-0277.

4 Trends in Income Dynamics for Aggregate and Granular Populations

In addition to understanding the shape of earnings distributions, researchers would also like to know about how individuals move through them. This is a much more demanding analysis, requiring a panel dimension to the data (at a minimum) and sufficiently large samples to estimate highly variable changes (ideally). Tracking changes in cross-sectional estimates of different percentiles of the income distribution - as in the previous section's analysis - can provide a sense of how growth varies across the distribution. However, because people do not remain at the same percentile of the income distribution over time, changes in percentile values do not necessarily align with the income growth experienced by specific people in different parts of the income distribution. The panel dimension of the data underlying IDDA permits the construction of within-person income growth statistics by initial income level, providing detail on how income growth experiences differ across the income distribution. IDDA also has sufficiently large samples to measure conditional income dynamics statistics for many demographic groups.

4.1 Percentiles of Income Growth over Time

A limited set of income growth measures can be constructed from publicly available sources, such as longitudinally linked Current Population Survey data, but the reliability of these estimates for smaller groups or nonstandard moments of the distribution is an open question. Attrition, item non-response, and other challenges could also influence survey-based estimates for groups of any size. As we did in the previous section, we begin by comparing basic income dynamics measures in IDDA against analogously constructed measures from the CPS. This helps illustrate the advantages of IDDA relative to other publicly available sources for studying income dynamics.[28]

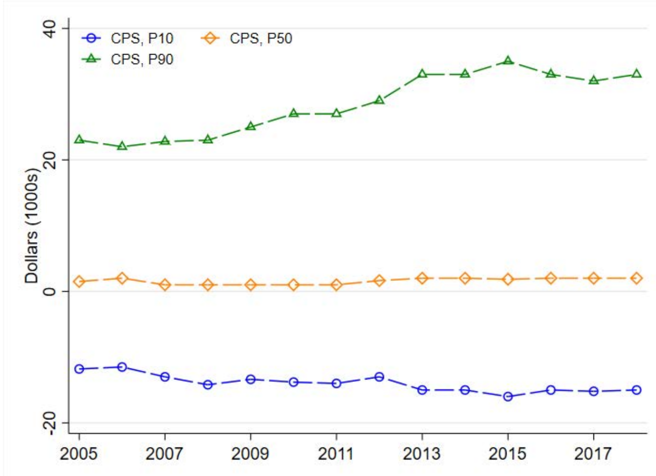
Figure 5 plots measures of income growth based on IDDA data, as well as corresponding measures constructed from the CPS. Panels (a) and (b) show selected percentiles of the wage and salary income growth distribution, estimated using the CPS and IDDA, respectively, for people initially in the 26th through 50th percentiles of the income distribution, a group for which measurement challenges related to especially high and low incomes are less likely to be relevant.

[28] The Panel Study of Income Dynamics (PSID) is another publicly available data source that can be used to construct measures like those discussed in this section. The PSID, which began in 1968, features longer panels than other surveys, but its granularity is limited by small sample sizes.

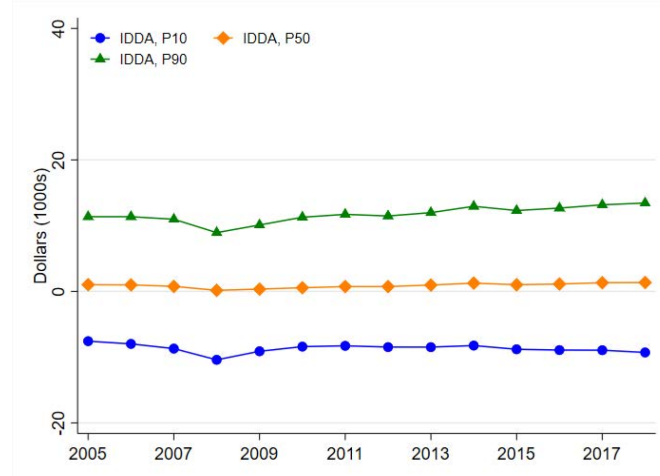
Median growth aligns reasonably well across data sources for the group initially earning in the second quartile. The differences between the two sources are much more pronounced in the tails of the growth distribution. Early in the period considered, the CPS shows 90th percentile wage and salary income growth in this quartile that is about twice as fast as that shown in IDDA, and that gap increases over time. At the other extreme, the 10th percentile of growth is consistently more than twice as negative as the 10th percentile of growth in IDDA. In summary, for people starting out in the second quartile of the income distribution, the CPS shows that the 10th percentile of growth is consistently lower than shown in IDDA, median growth is relatively comparable across data sources, and the 90th percentile of growth is consistently higher and growing faster over time.

Panels (c) and (d) reproduce panels (a) and (b) using AGI in IDDA and a similar income concept in the CPS. The takeaway is broadly similar, though the gaps between CPS and IDDA estimates of the 10th and 90th percentiles of growth are smaller in dollar terms when using AGI instead of wage and salary income. Aside from the change in income concept, the underlying samples also change from panels (a) and (b) to panels (c) and (d). In panels (a) and (b), each person must be observed and employed in consecutive years in order for income growth to be calculated. In panels (c) and (d), each person only has to be observed in a household in consecutive years. The broader sample, additional income sources included in AGI, and greater ability to capture extensive margin employment changes using a household income concept could all contribute to smaller gaps between IDDA and CPS in panels (c) and (d), although the impact of these differences on the relative magnitude is unclear a priori.

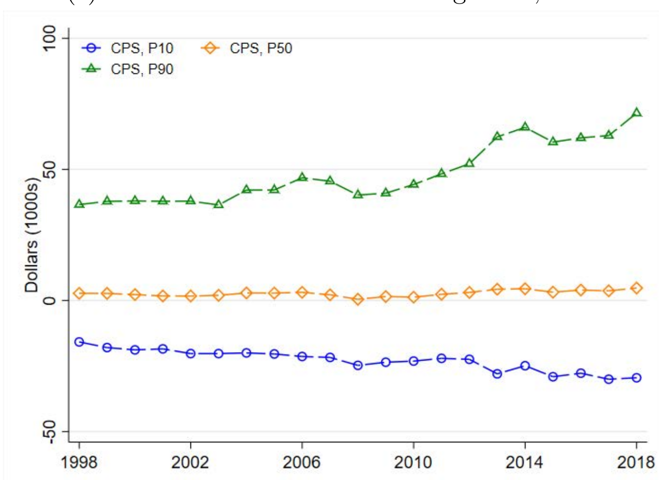
(a) Percentiles of individual wage and salary income, CPS



(b) Percentiles of individual wage and salary income, IDDA



(c) Percentiles of household AGI growth, CPS



(d) Percentiles of household AGI growth, IDDA

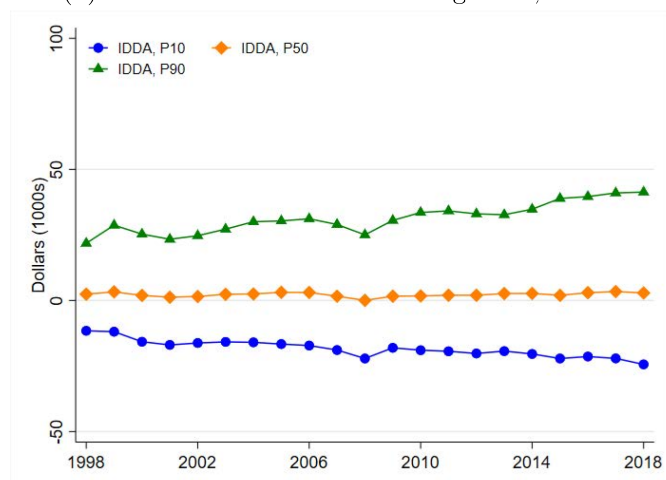


Figure 5: Select income growth measures, CPS vs. IDDA

Source: CPS, IDDA and authors' calculations.
Note: Values are in nominal dollars. Adjusted gross income (AGI) in panel (d) is aggregated to the household level by summing across tax returns filed from the same address. Wage and salary income in other panels is aggregated across employers within person. Growth measures are computed at the individual level. Growth is calculated among people with income in the 26th through 50th percentiles of base year income. Release authorization CBDRB-FY23-0277.

4.2 Granular Conditional Income Growth

Returning to wage and salary income, Figure 6 illustrates how median growth differs between data sources for subgroups defined by initial earnings throughout the distribution, instead of how different percentiles of the growth distribution differ within a single initial earnings quartile. It shows median annual growth for people with base year incomes at higher and lower points in the income distribution, by data source. The CPS shows faster growth than IDDA for people with lower initial incomes, whose incomes are rising at the median. The CPS also shows sizable declines at the median for people with higher initial incomes, while IDDA shows modest increases at the median, a notable divergence across data sources.[29] Together with Figure 5, this view of income growth across all percentiles of the distribution suggests a tendency of the CPS to spread out the distribution of income changes relative to that in IDDA, and produce larger magnitude estimates of both increases and decreases in income, rather than simply shifting the distribution by some fixed amount.

Consistent with both this tendency to measure larger gains and losses and the CPS's smaller sample sizes, CPS estimates are substantially more variable within states. Panel (a) of Figure 7 shows the standard deviation within each state over time of median income growth estimates by base year income by average state population over the period considered. Within IDDA, variability is higher in the top quartile of initial income but generally low across income groups and consistent within income group over population levels. CPS standard deviations vary more substantially with population, with smaller states seeing higher standard deviations, especially for the top quartile of base year income.

Panel (b) of Figure 7 plots these same standard deviation measures from the CPS (on the y-axis) against those from IDDA (on the x-axis), grouped by initial income quartile. In all states and across all income levels, the CPS standard deviation is greater than the IDDA standard deviation, often by a large margin. This is apparent from the different scales on the two axes; the 45-degree line is also plotted for comparison. Within the bottom three quartiles of base year income, the

[29] The median decline in earnings in the top decile in the CPS in Figure 6 is surprisingly large and grows over time. Much of this is driven by records with topcoded or imputed income information. Removing those records maintains the tendency of the CPS to show declines among top earners but shows much smaller median declines in growth for people with base year income in the top decile, and a much less pronounced trend over time. See Appendix Figure A.7.

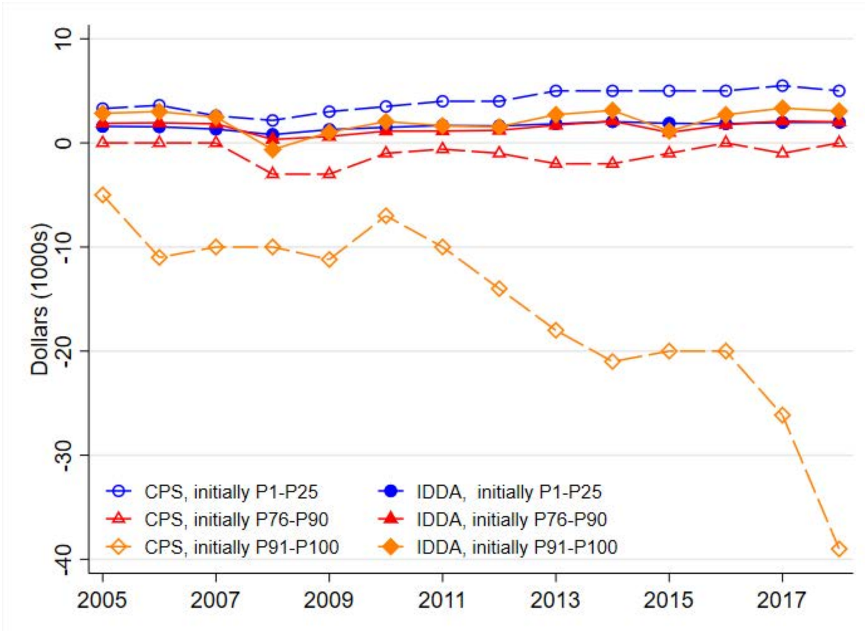


Figure 6: Median annual wage and salary income growth by base year income

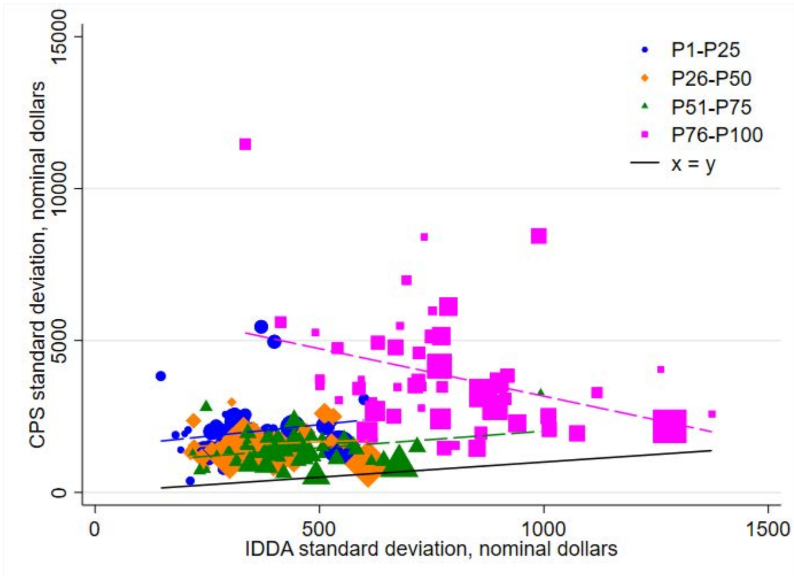
Source: CPS, IDDA and authors' calculations.
Note: Values are in nominal dollars. Growth measures are computed at the individual level. Release authorization CBDRB-FY23-0277.

correlation between standard deviations from CPS and IDDA is positive. Within the top quartile of base year income, however, the sign flips, and states with lower standard deviations in IDDA tend to have higher standard deviations in the CPS. Similarities in standard deviations of income growth across the two sources are limited, but the pink cloud on the right shows that earnings variability is higher in both sources for the highest earners. In sum, variability in estimates of earnings dynamics measures is generally much higher in the CPS than in IDDA, and the sources often differ markedly on measures apart from median growth. We conclude that using the CPS to study earnings dynamics, as opposed to IDDA, can lead to meaningfully mischaracterized dynamics in many cases.

4.3 Income Growth by Race and Ethnicity from IDDA and the CPS

Having compared income growth over the initial earnings distribution in IDDA and the CPS, we next ask how income growth evolves for the race and ethnicity groups in Section 3. Figure 8 shows median annual growth for prime-age workers by data source and race and ethnicity, revealing consistently faster growth in CPS estimates for White earners, but also noisier trends and larger

(a) Standard deviation of state median wage and salary income growth by starting income and state population



(b) Standard deviation of state median wage and salary income growth by starting income (markers weighted by state population)

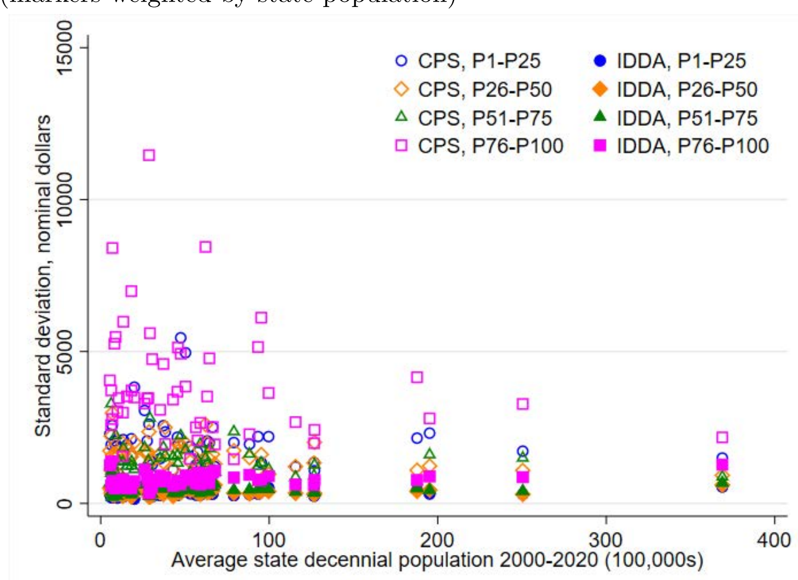


Figure 7: Variation in income growth measures, CPS vs. IDDA

Source: CPS, decennial census, IDDA and authors' calculations.
Note: Panel (a) plots the IDDA and CPS standard deviation of the across-year distribution of median salary and income growth, grouped by income quantile and state, (n = 200). Panel (b) groups observations by source and graphs average state decennial population against standard deviation values (n = 400). Values are in nominal dollars. Underlying median growth measures are calculated at the individual level, using wage and salary income aggregated across employers within person. Release authorization CBDRB-FY23-0277.

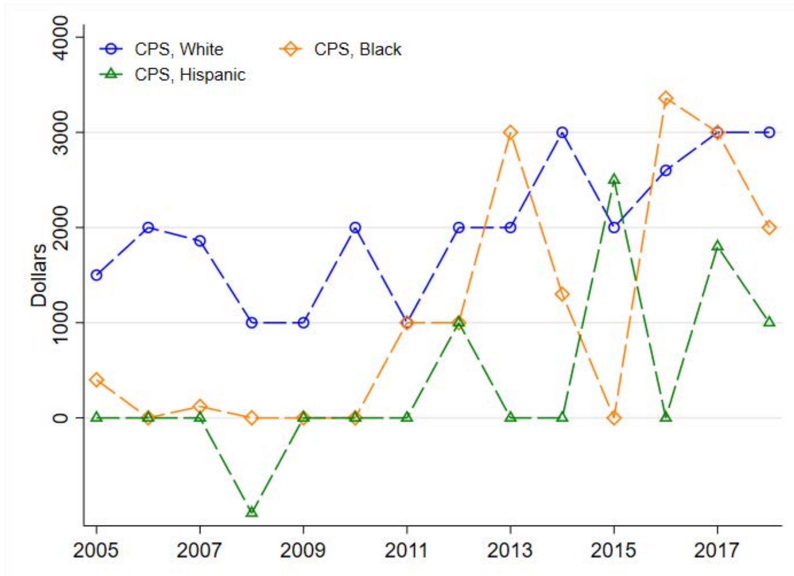
differences across groups than those in IDDA. IDDA shows modest median growth for all groups that declined during the Great Recession before gradually recovering over the subsequent years. The CPS shows much larger gaps between groups in any given year as well as growth trends that diverge much more substantially than those in IDDA, which are similar for all groups. Estimates for the smaller race/ethnicity groups in the CPS also see larger year-to-year fluctuations in growth than do the corresponding estimates from IDDA.

With the much larger sample sizes available in administrative data, IDDA allows for consideration of income growth in detail across a broader set of race/ethnicity and income groups than is feasible using the CPS. This could be especially helpful for understanding the changes in inequality discussed in Section 3. In particular, non-Hispanic Black men have seen uniquely acute declines in earnings relative to non-Hispanic White men since the Great Recession. How did these compare to earnings dynamics for other non-White groups of men? Do the patterns differ across initial earnings quantiles?

Panel (a) of Figure 9 plots one-year earnings growth in wage and salary income by race and ethnicity and by initial earnings percentile. It reveals that one-year earnings growth for Black earners over this period is on par with typical earnings growth, conditional on initial earnings below the 75th percentile. At higher percentiles, earnings growth for Black earners is comparable to that for AIAN earners and lags that for all other race and ethnicity groups. Panel (a) also shows relative declines in growth for Black earners that are most notable in 2010–2012 and among those with initial incomes in the top 10 percent. It also shows similar but smaller declines in growth among Black earners initially in the 76th through 90th percentiles and the 51st through 75th percentiles. Over a five-year horizon, shown in Panel (b) of Figure 9, earnings growth for Black earners was again broadly in line with AIAN earners and consistently slower than growth for White and Asian earners across starting income groups, and any shifts in growth around the Great Recession are less stark. A second striking fact that emerges from this panel is that since 2005, five-year earnings growth has consistently been fastest for Asian earners at all income levels, with the largest relative gains in growth coming for the highest earners over this period.

The patterns in earnings growth reveal that Black earners experienced gaps in the level of growth, particularly over longer horizons, combined with a larger and more persistent slowdown in earnings growth after the Great Recession. While not definitive, this analysis suggests that

(a) Median wage and salary income growth by race, CPS



(b) Median wage and salary income growth by race, IDDA

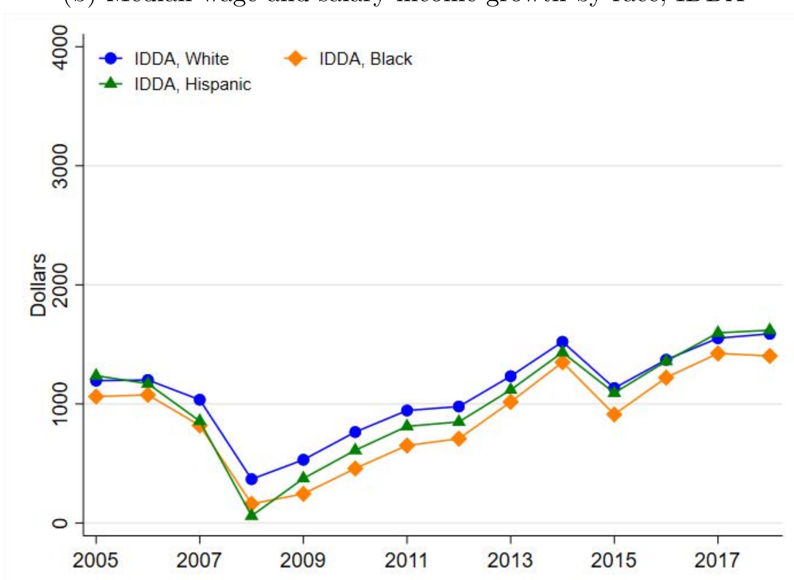
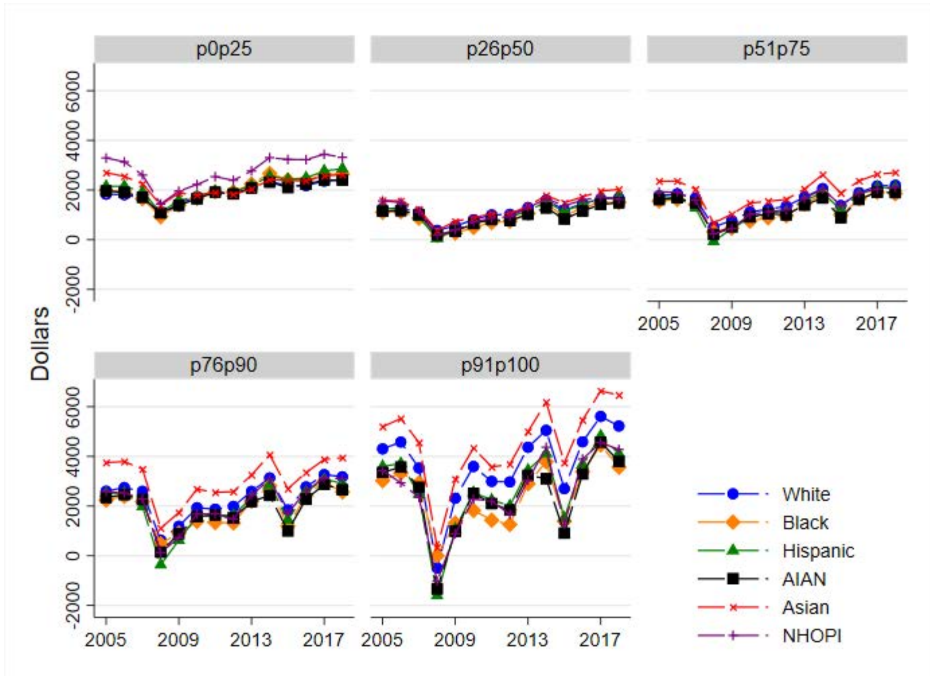


Figure 8: Median annual wage and salary income growth by race/ethnicity, CPS vs. IDDA

Source: CPS, IDDA and authors' calculations.
Note: Values are in nominal dollars. Growth measures are computed at the individual level. Unless otherwise indicated, growth is calculated among prime-age workers with income in the 26th through 50th percentiles of base year income. Ethnicity is non-Hispanic unless otherwise specified. Release authorization CBDRB-FY23-0277.

(a) One-year growth



(b) Five-year growth

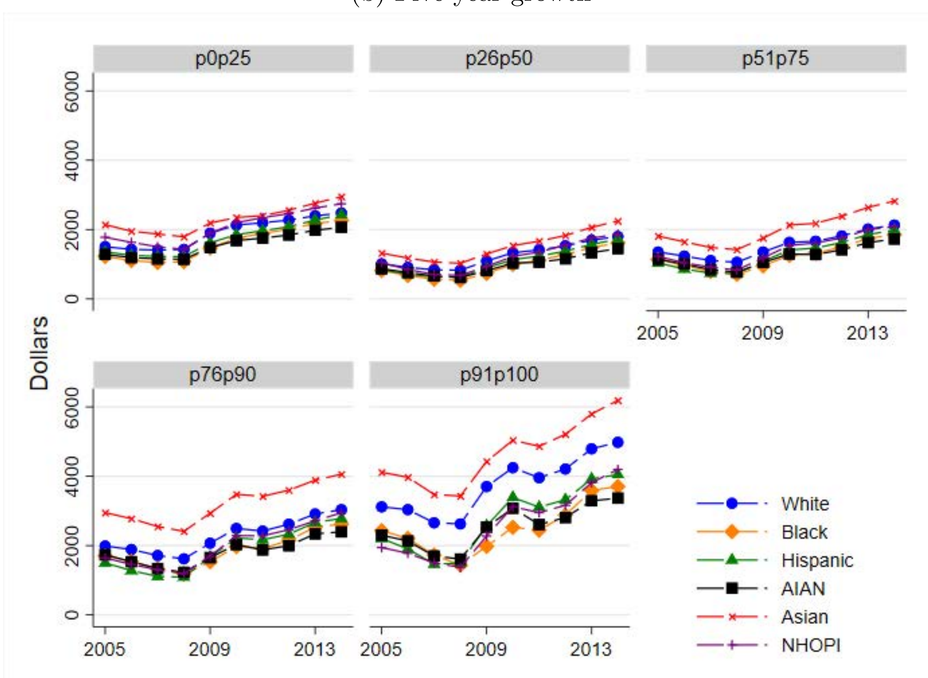


Figure 9: Median wage and salary income growth by starting income and race/ethnicity, IDDA

Source: CPS, decennial census, IDDA and authors' calculations.
Note: Values are in nominal dollars. Underlying median growth measures are calculated at the individual level for prime-age workers using wage and salary income aggregated across employers within person. Ethnicity is non-Hispanic unless otherwise specified. AIAN abbreviates American Indian or Alaska Native. Release authorization CBDRB-FY23-0277.

earnings growth among higher-earning Black people may contribute to the decline in relative earnings identified for this group in Section 3.

5 Distribution and Growth in Native Incomes in IDDA

IDDA is unique among publicly available data sources for allowing analysis of income distributions and their evolution for Native people and in Native land areas. As a final application, we extend the analysis of previous sections to these groups. In most cases, it is not possible to compare the patterns we identify with other sources or earlier literature, so we present them independently, using only statistics from IDDA.

IDDA includes nearly 800,000 state- and U.S.-level statistics describing income levels and mobility for non-Hispanic individuals who identify as American Indian or Alaska Native or as Native Hawaiian or other Pacific Islander. By providing these estimates at the subnational level, IDDA builds on the demographic granularity in Akee et al. (2019). Those authors used linked Census-IRS data to summarize national trends in income inequality and mobility for race and ethnicity groups, including AIAN and NHOPI individuals, and their paper is an important exception to the limited literature on the question of Native earnings distributions.

In addition, IDDA includes a supplement containing over 70,000 statistics describing incomes for both Native and non-Native populations living in Native areas. These include all American Indian and Alaska Native areas and Native Hawaiian Homelands as delineated by the Census Bureau in 2017, reported as one aggregate geography. To construct statistics for this supplement, we start with the 1040 and W-2 samples described in Section 2 and identify individuals living in Native areas, using residential address information from the Master Address File-Auxiliary Reference File. Instead of the single race and ethnicity variable used at the state and U.S. level, we use a broad definition of Native identity that includes individuals who identify any of their races as American Indian, Alaska Native, Native Hawaiian, or other Pacific Islander, regardless of Hispanic ethnicity. We prioritize sources that allow respondents to identify multiple races, using the most recent American Community Survey or decennial Census (2010 or 2000) in which race/ethnicity is reported.[30] Aside from sample differences, construction of statistics in the supplement follows

[30] Liebler et al. (2016) show that many individuals changed American Indian or Alaska Native response categories from the 2000 to the 2010 census, moving between single- and multi-racial categories or in and out of the AIAN label.

those for other geographies in IDDA.

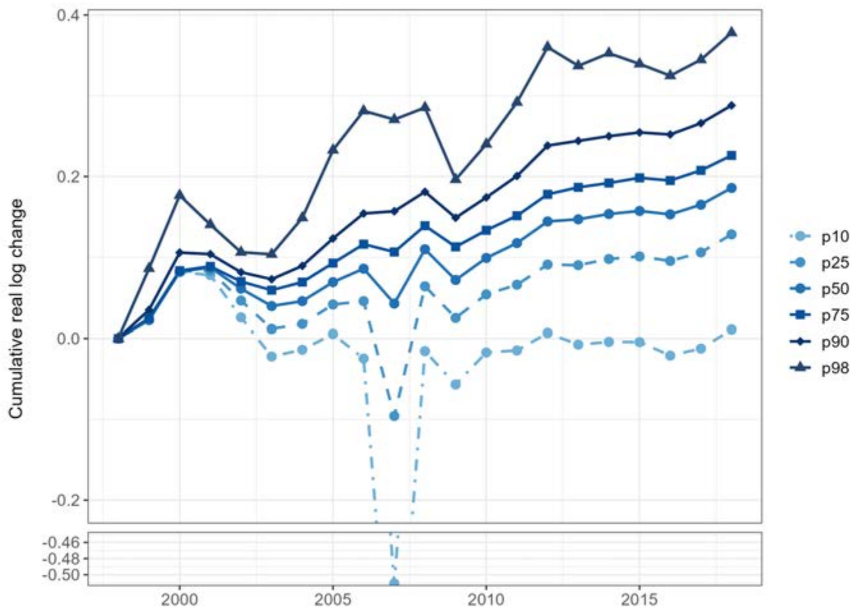
Using statistics defined for Native areas, we reproduce our baseline analysis of cumulative changes in household income and individual earnings for individuals living in Native areas. Figure 10 presents the results. Comparing these to Figures 1 and 2 shows that Native areas share some key features of income and earnings growth with the U.S.-level IDDA data series. First, panel (a) shows that as in the U.S. broadly, household incomes in Native areas "fanned out" over the 1998 to 2018 period: incomes grew more at the top of the distribution than at the bottom. The ratio of the 90th to 10th percentile of household income rose from 8.4 to 11, mirroring the U.S.-level increase (shown in Appendix Figure A.1) almost exactly. The 98th/50th percentile ratio increased from 4.3 to 5.3. Second, across the distribution, the total percent change in household income from 1998 to 2018 was similar to the corresponding U.S.-level change, within a few percentage points. However, the timing of this growth differs. In the U.S. overall, at the median and below, household incomes were flat or falling from 2001 through the Great Recession, but showed sustained growth in the subsequent recovery. In contrast, the 10th-50th percentiles in Native areas showed rapid growth before 2001 and had started to climb again in the run-up to the Great Recession—but increased more slowly through the recovery. Even at higher percentiles, relative to growth at the U.S. level, income growth appears to have slowed in the late 2010s.

Panel (b) reports results on the same percentiles using the W-2 statistics on individual earnings. In the years leading up to the Great Recession, growth in individual earnings in Native areas also outpaced growth at the U.S. level, particularly at the bottom of the distribution. The 10th and 25th percentiles of earnings never fell below their 2005 level, while still realizing relative growth after 2010. At the 10th percentile, individual earnings grew nearly 20 percent from 2010 to 2018, compared with 8 percent at the median. Meanwhile, top earners saw a decline in W-2 earnings after 2015. The result is a slight narrowing of the earnings distribution over time, similar to that observed in the U.S. broadly, but with some unique recession dynamics.

Understanding the big-picture evolution of incomes in Native areas is an important contribution of IDDA, given the limited availability of alternative data sources. But IDDA's demographic

IDDA takes the most recent race response observed for each PIK and uses that response for all data years. In 2010, about 15 percent of individuals in the Native areas 1040 sample and 20 percent of individuals in the Native areas W-2 sample identified as Native. The age and gender composition of the IDDA Native areas sample is reported in Appendix Table A.5.

(a) Cumulative log changes in Household AGI



(b) Cumulative log changes in individual earnings

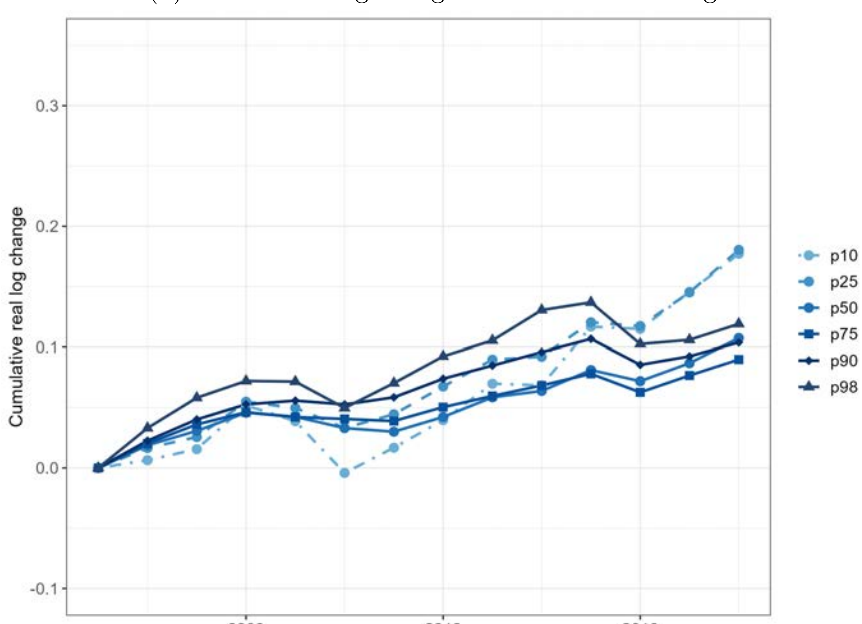


Figure 10: Household income and earnings growth in Native areas

Source: IDDA and authors' calculations.
Note: The IDDA Native areas geography includes individuals living in American Indian and Alaska Native areas or Native Hawaiian Homelands as delineated by the Census Bureau. Data period is 2005-2018 for individual earnings and 1998-2018 for household income. We choose not to compare total income growth through 2019 due to changes in tax filing related to the Covid-19 pandemic. The large decline in household income in 2007 is similarly related to filing changes, as discussed in Section 3. Release authorization CBDRB-FY23-0373.

granularity allows us to go further and disentangle trends affecting tribal lands from those affecting Native earners. For instance, Akee et al. (2019) show that AIAN tax filers experience income gaps along the distribution and are more likely to experience downward income mobility than White earners. Do Native earners living in tribal areas experience a larger or smaller earnings gap than all AIAN earners? Within Native areas, do Native and non-Native individuals show similar patterns in income growth? IDDA provides the tools to answer these and similar questions at the intersection of place and identity.

Figure 11 shows how relative median earnings have changed over time for Native and non-Native earners in tribal areas, as well as for all AIAN and NHOPI earners. Each value is expressed as a percentage of the U.S. population median. Large disparities in earnings levels immediately stand out. Earnings in Native areas are lower than those in the rest of the U.S., and earnings for Native people in Native areas are lower than for AIAN and NHOPI earners elsewhere. In 2005, median earnings for Native workers living in Native areas were two-thirds of the U.S. median, compared with 70 percent for all AIAN earners and over 90 percent for all NHOPI earners. Note that the group of all AIAN earners includes individuals living in tribal areas who identify as single-race American Indian or Alaska Native (i.e., the blue line contains some but not all of the population represented by the orange line), and likewise with the group of NHOPI earners. The earnings differential between Native earners inside and outside of tribal areas may therefore be larger than the figure suggests.

Within Native areas, non-Native earners experienced a substantial earnings privilege, about 20 percentage points. It is also striking that these groups saw distinct earnings trajectories. Before the Great Recession, relative earnings for both Native and non-Native earners living in Native areas were increasing, consistent with Figure 10. In 2010, relative earnings fell sharply for Native earners living in Native areas. Meanwhile, earnings for non-Native earners in tribal areas and for all AIAN earners continued to move toward the U.S. median. By 2013, the gap in earnings between Native and non-Native earners had increased by 5 percentage points. After 2013, this period of widening inequality within Native areas appears to give way to a period of broad-based divergence between Native areas and the rest of the U.S., as relative earnings declined for both Native and non-Native workers living in Native areas.

The trends shown in Figure 11 are concerning and contrast with the long-run convergence of

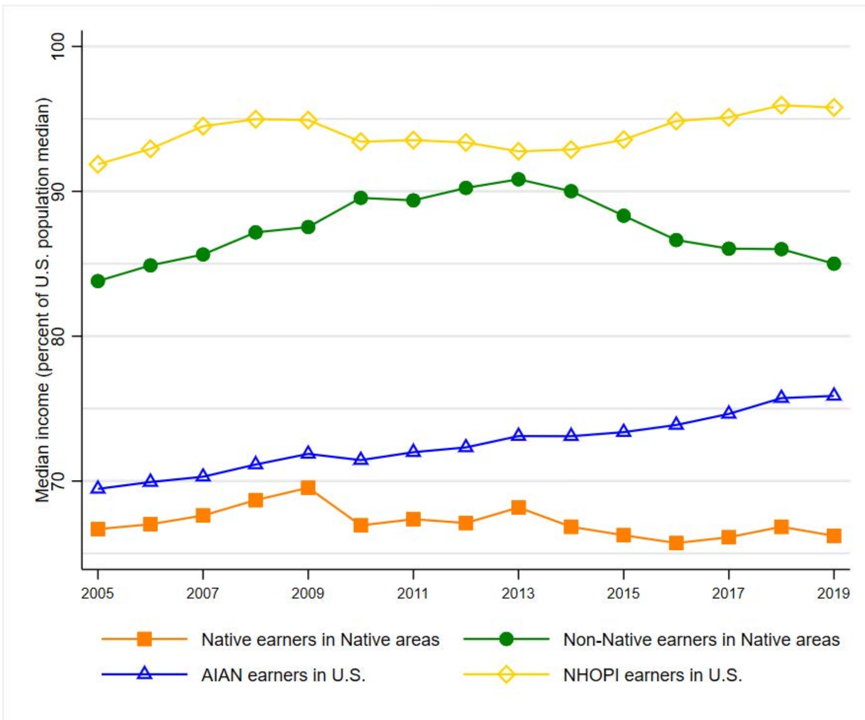


Figure 11: Median earnings in Native areas and for Native groups, relative to U.S. population

Source: IDDA and authors' calculations.
Note: Each point plots relative median earnings in the given race and ethnicity group, expressed as a percentage of the U.S. population median. The groups of all American Indian or Alaska Native earners and all Native Hawaiian or other Pacific Islander earners include some individuals living in Native areas who identify only as single-race, non-Hispanic AIAN, or NHOPI. Release authorizations CBDRB-FY23-0373 and CBDRB-FY23-0277.

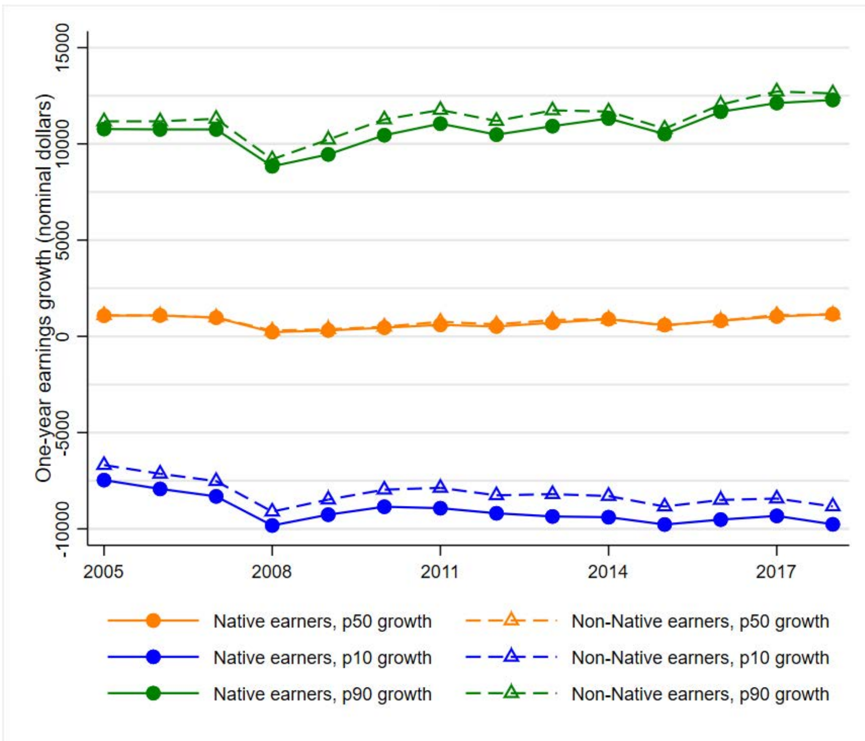


Figure 12: Distribution of Earnings Growth for Native and non-Native earners in Native Areas

Source: IDDA and authors' calculations.
Note: Each point shows the 10th, 50th, or 90th percentile of one-year earnings growth among Native and non-Native earners initially in the second quartile of the earnings distribution in Native areas. Initial year earnings quartiles are defined within a sample and geography but across demographic groups. Measures of earnings growth are computed among earners who remain in the W-2 sample and live in a Native area in both years. All values are in nominal dollars. Release authorization CBDRB-FY23-0373.

tribal incomes following the 1975 Indian Self-Determination and Education Assistance Act (Akee, 2021). But Native economies are unique, and economic activity outside of wage employment may play an important role.[31] Figure 11 also raises the question of whether Native and non-Native people living in Native areas experience different trends in migration, employment, or movement through the income distribution. Our final figure uses the one-year earnings growth measures highlighted in section 4 to explore one of these dimensions. However, the transition matrix module makes available information on conditional migration and employment flows for earners along the distribution.

Figure 12 shows the 10th, 50th, and 90th percentiles of earnings growth for Native and non-Native earners initially in the second quartile of the earnings distribution in Native areas. Median earnings growth in this group looks very similar for Native and non-Native earners, despite their different earnings levels and trajectories. However, looking at the full distribution of earnings growth shows that low growth is lower and high growth is slightly less high for Native earners than for non-Native earners in this quartile.[32] These differences are potentially large, particularly for those experiencing earnings losses: the loss at the 10th percentile of growth was 8 to 14 percent larger for Native earners than for non-Native earners. The gaps in earnings growth (or loss) also widened slightly from 2009 to 2013, the period of widening earnings inequality between Native and non-Native earners, but these trends are obscured by the much larger within-group differences between low and high earnings growth.

Together, these IDDA statistics add to the description of AIAN incomes provided in Akee et al. (2019), showing that median earnings are lower for Native earners living in Native areas than for AIAN earners throughout the U.S. and that this disparity has increased since the Great Recession. We identify distinct patterns in the distribution of earnings and earnings growth that are not explained by place or Native identity alone, but can be seen only at the intersection of these characteristics.

[31] For instance, median household income among Native tax filers in Native areas remained relatively stable until 2013, shown in Appendix Figure A.8. Gubbay and Trostle (2023) discuss these trends in the context of the multifaceted economic landscape in Native areas. Self-employment, entrepreneurship, and subsistence economies are important and established parts of many tribal economies.

[32] Initial year earnings quartiles are defined across demographic groups. These patterns hold for earners initially in the third quartile of the distribution, capturing those just above and below the overall median.

6 Conclusion

Considering income inequality and dynamics within granular demographic and geographic cells can reveal important facts about how inequality evolves in the U.S. This approach also has the potential to enhance our understanding of the functioning of the broader economy, as economists turn to questions about potentially time-varying causes behind the changes we observe and to questions about the impacts these distributions and their dynamics have on other outcomes. To contribute to this agenda, we developed a set of statistics describing income distributions, income mobility, and conditional income growth for communities in the U.S. defined by place (U.S. states) and demographics (race and ethnicity, sex, age, and birthplace). We used the universe of 1040 tax filings from 1998 to 2019 as well as the universe of W-2 filings for 2005 to 2019 to construct measures that reflect earnings distributions in these two populations. We label the resulting analytical dataset the Income Distributions and Dynamics in America data, or IDDA.

In this paper, we investigate what this approach reveals about patterns of evolving income inequality for groups defined by race and ethnicity, and we compare it with what can be observed in public sources. We find that gross features of U.S.-level earnings distributions, like 75-25 percentile inequality, align well across the measures we construct from tax records and those that could be constructed using publicly available self-reports of earnings from survey data. But we find that public sources reproduce distributional patterns for subnational groups with a low level of fidelity. Also, inequality in the earnings distribution is generally imprecisely captured using public data for the highest earnings percentiles. We also find that even standard measures of distributional features for race and ethnicity groups at the state level benefit from the large samples available in administrative data. Furthermore, the administrative data allow for construction of a longitudinal record of individual earnings. From these, we derive measures of earnings dynamics that cannot be constructed elsewhere. We show that earnings dynamics measured with the administrative panel data differ substantially from those inferred from changes in earnings at percentiles of the cross-section of earnings in survey data.

Finally, to demonstrate the breadth of potential future analysis, we present two applications of IDDA statistics. In the first application, we find that since the Great Recession, at most percentiles in the upper half of the distribution, labor earnings for Black men and Black women have declined relative to those for White men in contrast to relative gains for most other race, ethnicity and sex groups. In the second application, we find that the earnings trajectories for Native people residing inside Native areas and the trajectories of those living outside them diverged after the Great Recession.

Much work remains to be done to provide a comprehensive view of how income and earnings distributions evolve for race, ethnicity, and other demographic groups in subnational communities across the U.S. This paper has examined this topic from only a few angles. However, the wealth of information in IDDA provides several new insights in the space of even this single investigation. We encourage other researchers to use this and other newly available resources to begin addressing these questions more deeply.

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A Additional Figures and Tables

Table A.1: Educational attainment by demographic characteristics, ACS Estimates

(a) 4-year college attainment (2005)

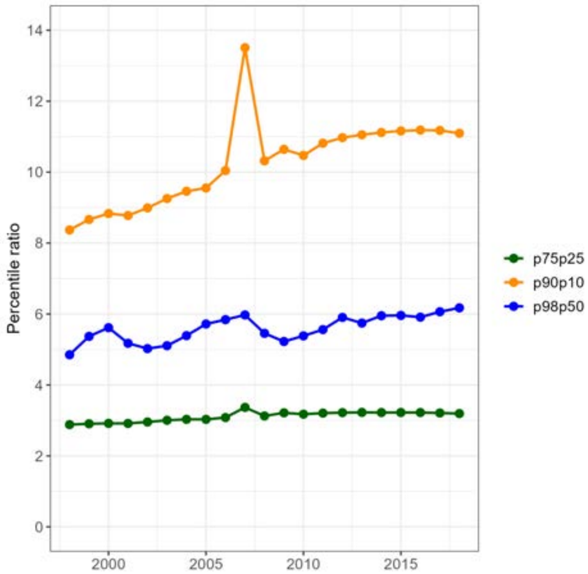
Race/Ethnicity	Female	Male
Hispanic	15.0%	11.0%
NH AIAN	17.2%	14.7%
NH Asian	50.0%	54.2%
NH Black	20.7%	17.9%
NH NHOPI	16.6%	17.3%
NH Other	27.0%	24.3%
NH White	32.0%	31.7%

Data from the 2005 ACS. Table records the bachelor's degree attainment rate for the specified group. Sample is of members of the specified group between the ages of 25 and 54 whose annual earnings are at least equivalent to working half-time for 13 weeks at the federal minimum wage. Statistics are weighted.

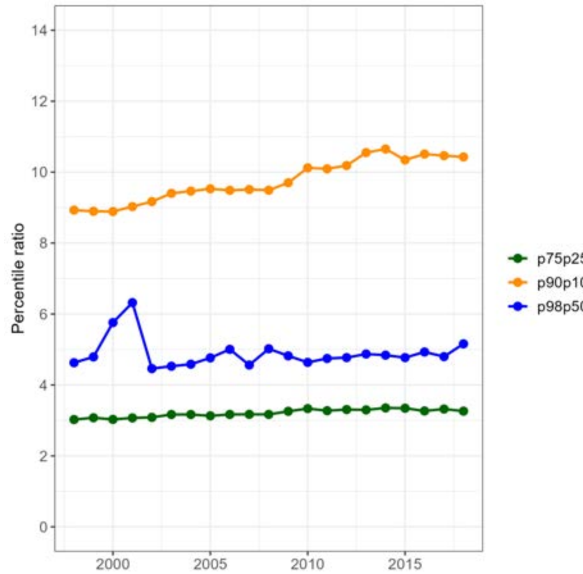
(b) Δ in 4-year college attainment (2005 to 2019)

Race/Ethnicity	Female	Male
Hispanic	48.7%	43.6%
NH AIAN	24.4%	3.4%
NH Asian	18.8%	11.6%
NH Black	41.1%	25.1%
NH NHOPI	28.3%	9.8%
NH Other	43%	32.9%
NH White	34.1%	18.9%

Data from the 2005 and 2019 ACS. Table records the percentage change in bachelor's degree attainment rate for the specified group. Sample is of members of the specified group between the ages of 25 and 54 whose annual earnings are at least equivalent to working half-time for 13 weeks at the federal minimum wage. Statistics are weighted.



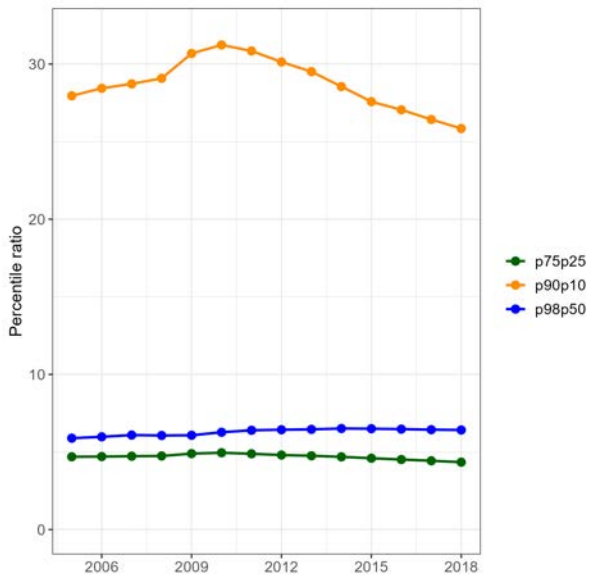
(a) IDDA household income percentile ratios



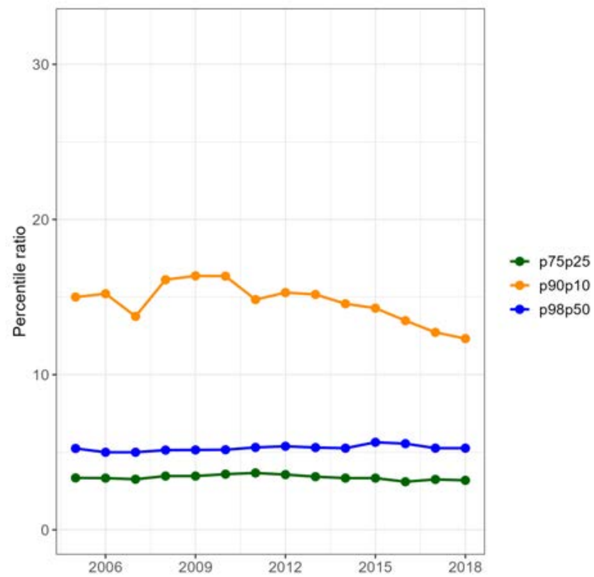
(b) CPS household income percentile ratios

Figure A.1: Household income percentile ratios in IDDA vs CPS

Source: IDDA and IPUMS CPS.
Note: CPS statistics calculated by the authors following IDDA documentation and using the sample of all ASEC respondents aged 16 and over. Data period for both sources is 1998 to 2018. Release authorization CBDRB-FY23-0277.



(a) IDDA individual earnings percentile ratios



(b) CPS individual earnings percentile ratios

Figure A.2: Individual earnings percentile ratios in IDDA vs CPS

Source: IDDA and IPUMS CPS.
Note: CPS statistics calculated by the authors following IDDA documentation and using the sample of all ASEC respondents aged 16 and over who reported positive wage income. Data period for both sources is 2005 to 2018. Release authorization CBDRB-FY23-0277.

Table A.2: Changes in State-level Distributional Statistics by Race and Ethnicity: ACS total household income vs. IDDA household AGI (2000-2018)

Estimated slope $\Delta(y)^{state}_{ACS} = \beta\Delta(y)^{state}_{IDDA} + \varepsilon^{state}$

Group	(1) N	(2) log(p10)	(3) log(p25)	(4) log(p50)	(5) log(p75)	(6) log(p90)	(7) p90p25	(8) p98p50
All	51	0.359	1.075	1.107	1.099	1.064	0.744	1.948
		(0.159)	(0.080)	(0.039)	(0.026)	(0.031)	(0.056)	(0.174)
Hispanic	50	1.376	1.172	1.036	0.967	1.061	0.904	0.506
		(0.275)	(0.156)	(0.087)	(0.080)	(0.084)	(0.318)	(0.527)
AIAN	31	0.702	0.777	0.920	1.024	0.920	1.430	-0.314
		(0.403)	(0.284)	(0.227)	(0.192)	(0.175)	(0.618)	(1.184)
Asian	45	0.669	0.751	0.880	0.789	0.667	0.272	0.379
		(0.217)	(0.139)	(0.111)	(0.077)	(0.095)	(0.198)	(0.173)
Black	44	0.692	1.712	1.538	1.461	1.173	0.348	0.882
		(0.444)	(0.321)	(0.220)	(0.180)	(0.134)	(0.267)	(0.188)
NHOPI	3							
White	51	0.465	1.153	1.110	1.076	1.034	0.789	1.604
		(0.183)	(0.075)	(0.041)	(0.029)	(0.033)	(0.058)	(0.193)

Note: Changes are computed from 2000 (the first year of ACS data) to 2018. For NHOPI and Asian earners, changes are computed from 2002 to 2018 to match data availability for these groups in the CPS comparison in Table 6. We compute the 10th-90th percentiles of income for subnational populations with at least 50 observations in the ACS. We compute the 98th percentile of income for subnational populations with at least 250 observations in the ACS. Release authorization CBDRB-FY23-0277.
Source: IDDA and authors' calculation using IPUMS ACS. Release authorization CBDRB-FY23-0277.

Table A.3: Changes in State-level Distributional Statistics by Race and Ethnicity: ACS individual wage/salary income vs. IDDA W-2 earnings (2005-2018)

Estimated slope $\Delta(y)^{state}_{ACS} = \beta\Delta(y)^{state}_{IDDA} + \varepsilon^{state}$

Group	(1) N	(2) log(p10)	(3) log(p25)	(4) log(p50)	(5) log(p75)	(6) log(p90)	(7) p90p25	(8) p98p50
All	51	1.018	0.857	0.793	0.977	0.895	0.571	1.120
		(0.067)	(0.046)	(0.039)	(0.035)	(0.030)	(0.104)	(0.136)
Hispanic	49	0.327	0.452	0.936	1.257	1.312	-0.137	1.128
		(0.214)	(0.106)	(0.108)	(0.100)	(0.120)	(0.210)	(0.458)
AIAN	36	1.436	0.679	0.794	0.712	0.618	0.895	0.759
		(0.242)	(0.185)	(0.165)	(0.162)	(0.229)	(0.374)	(1.244)
Asian	45	0.290	0.533	0.538	0.718	0.773	0.528	1.157
		(0.254)	(0.119)	(0.086)	(0.073)	(0.109)	(0.254)	(0.561)
Black	43	1.071	0.859	0.496	0.812	0.788	0.616	0.762
		(0.132)	(0.092)	(0.147)	(0.153)	(0.131)	(0.106)	(0.267)
NHOPI	8	0.792	0.688	0.457	0.656	0.517	0.140	
		(0.736)	(0.539)	(0.233)	(0.391)	(0.571)	(0.418)	
White	51	0.911	0.863	0.884	0.930	0.880	0.606	1.670
		(0.068)	(0.055)	(0.042)	(0.038)	(0.029)	(0.135)	(0.261)

Note: Changes are computed from 2005 to 2018 for individual earnings. We compute the 10th-90th percentiles of income for subnational populations with at least 50 observations in the ACS. We compute the 98th percentile of income for subnational populations with at least 250 observations in the ACS. Release authorization CBDRB-FY23-0277.
Source: IDDA and authors' calculation using IPUMS CPS.

Table A.4: IDDA Prime-aged Working Sample Composition (2010)

Demographic Composition	Prime-age Working W2	Prime-aged Working CPS
Female	49.0%	47.4%
Male	51.0%	52.6%
Hispanic	13.5%	16.3%
Non-Hispanic AIAN	0.9%	0.6%
Non-Hispanic Asian	5.2%	5.7%
Non-Hispanic Black	12.1%	11.2%
Non-Hispanic NHOPI	0.2%	0.3%
Non-Hispanic Other	1.4%	1.2%
Non-Hispanic White	66.6%	64.7%
Foreign born	15.2%	18.0%
Not Foreign born	84.8%	82.0%
25-34	33.0%	33.1%
35-44	32.1%	32.5%
45-54	34.9%	34.4%

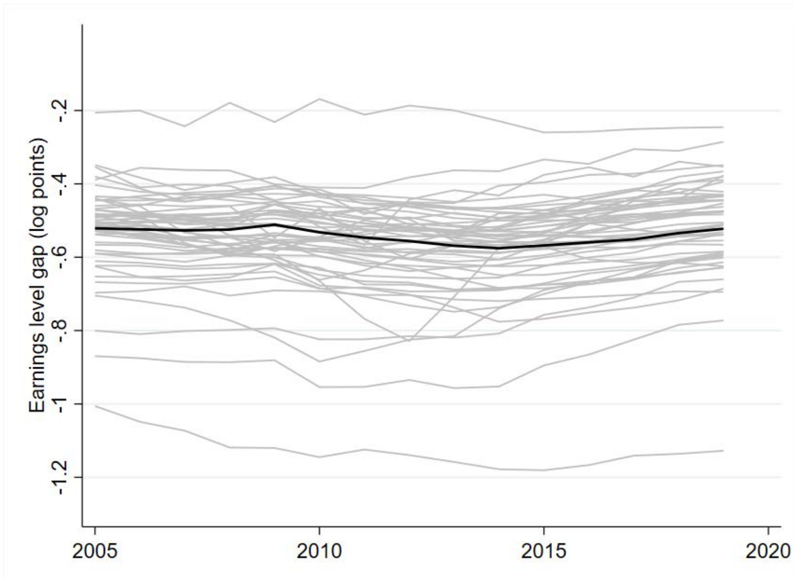
Source: IDDA and IPUMS CPS.
Note: The IDDA Prime-age working-W2 sample includes individuals aged 25-54 with earnings at least equivalent to working 20 hours a week for 13 weeks at the federal minimum wage. In 2010, this was $1,885. Individuals in the 25-54 age bracket made up 63 percent of the overall W-2 sample in that year. The earnings threshold is much less restrictive: $1,885 fell substantially below the 10th percentile of individual earnings, which ranged from $4,174 for the 25-34 year-old group to $7,601 for the 45-54 year-old group. Earnings are measured using wage compensation reported on form W-2. Release authorization CBDRB-FY24-0131.

Table A.5: IDDA Native Areas Data Source Composition (2010)

Demographic composition	Household-1040	Individual-W2
Female	51.9%	49.3%
Male	48.1%	50.7%
Native (AIAN or NHOPI)	14.6%	19.8%
Non-Native	85.4%	80.2%
16-24	10.3%	17.8%
25-34	19.1%	21.3%
35-44	17.6%	19.5%
45-54	20.1%	21.4%
55-64	17.3%	15.1%
65+	15.5%	5.0%

Source: IDDA.
Note: The Native Areas data source includes individuals whose residential address falls within an American Indian or Alaska Native area or Native Hawaiian Homeland, using Census Bureau delineations from 2017. Individuals are coded as Native if they identify any of their races as American Indian, Alaska Native, Native Hawaiian, or other Pacific Islander, regardless of Hispanic ethnicity. Release authorization CBDRB-FY24-0131.

(a) Earnings difference between median Black and White men by state



(b) Earnings difference between 90th percentile Black and White men by state

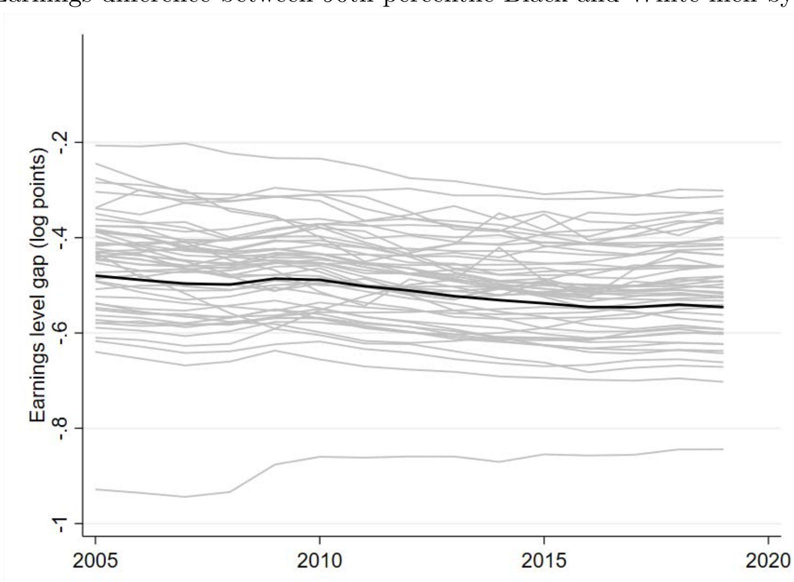
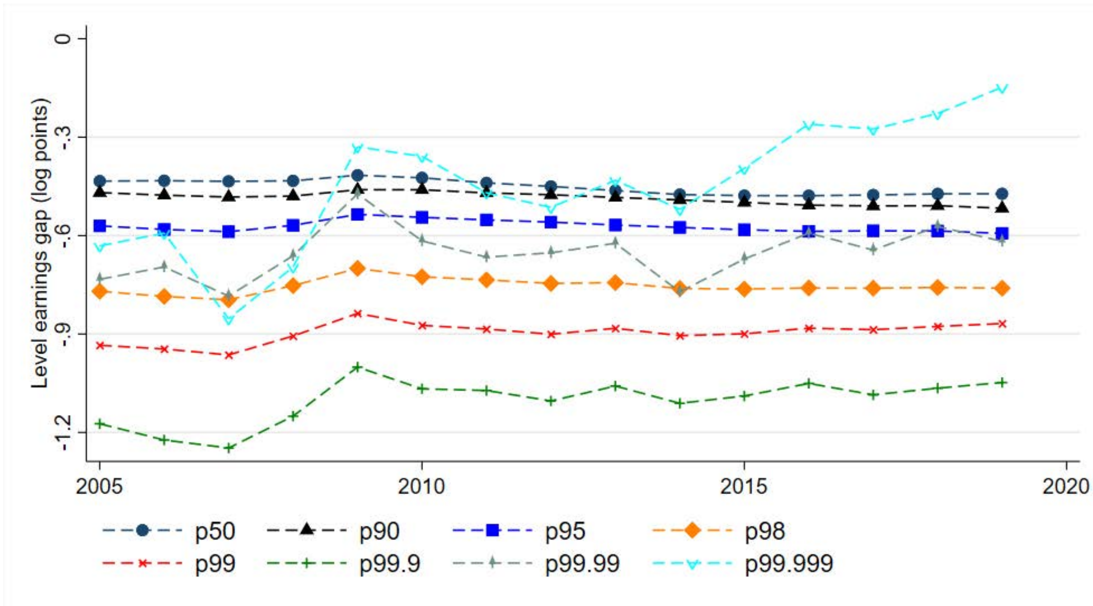


Figure A.3: Level earnings differences between Black and White men by state

Source: IDDA and authors' calculations.
Note: In panel (a), lines plot the log point difference in median annual earnings between Black and White male earners in each state. In panel (b), lines plot the log point difference in the 90th percentile of annual earnings between Black and White male earners in each state. The black line is for the total U.S.. Ethnicity is non-Hispanic unless otherwise noted. Release authorization CBDRB-FY23-0277.

(a) Gap between Black men and White men, top percentiles



(b) Gap between Black women and White men, top percentiles

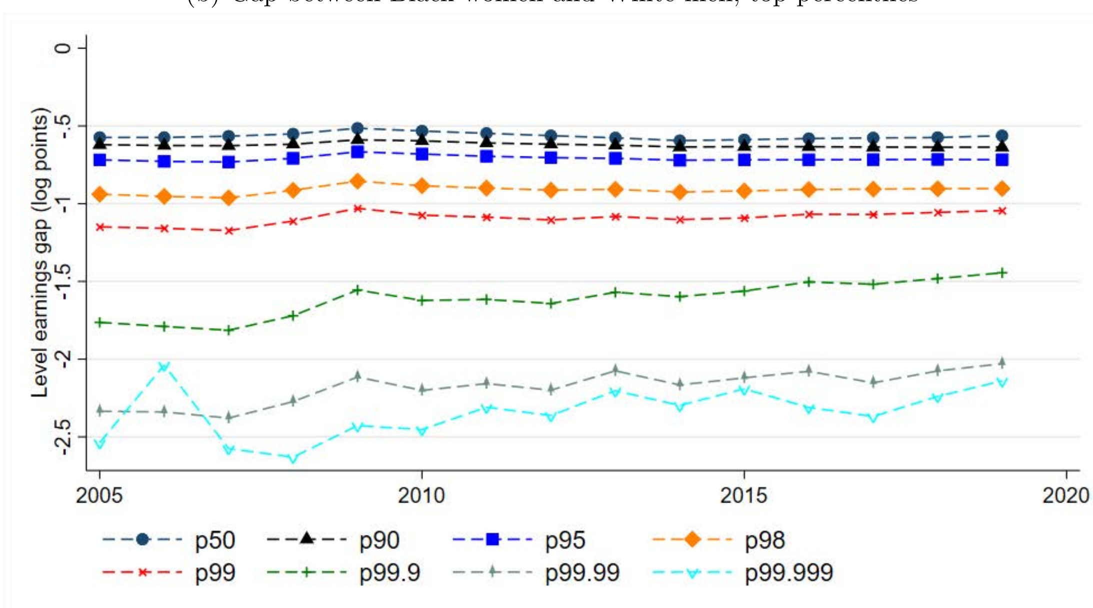
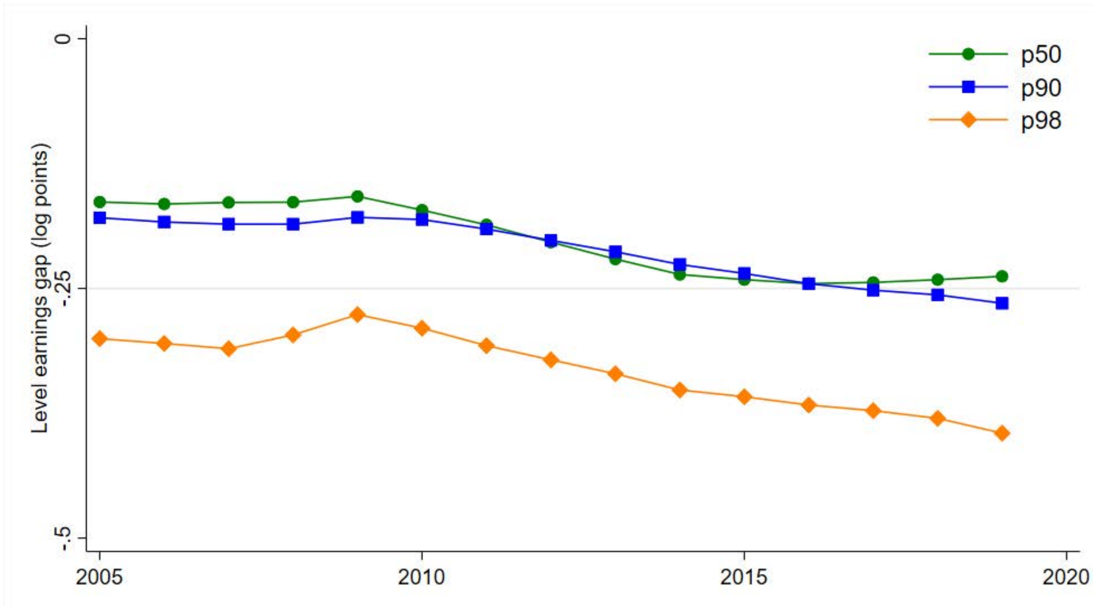


Figure A.4: Gap between Black earners and White men, top percentiles

Source: IDDA and authors' calculations.
Note: Each panel plots the earnings gap between prime-age Black earners and White men, in log points. Includes workers aged 25-54 with earnings at least equivalent to working 20 hours a week for 13 weeks at the federal minimum wage. Ethnicity is non-Hispanic unless otherwise specified. Release authorization CBDRB-FY23-0277.

(a) Gap between Black women and White women



(b) Gap between Black women and White women, top percentiles

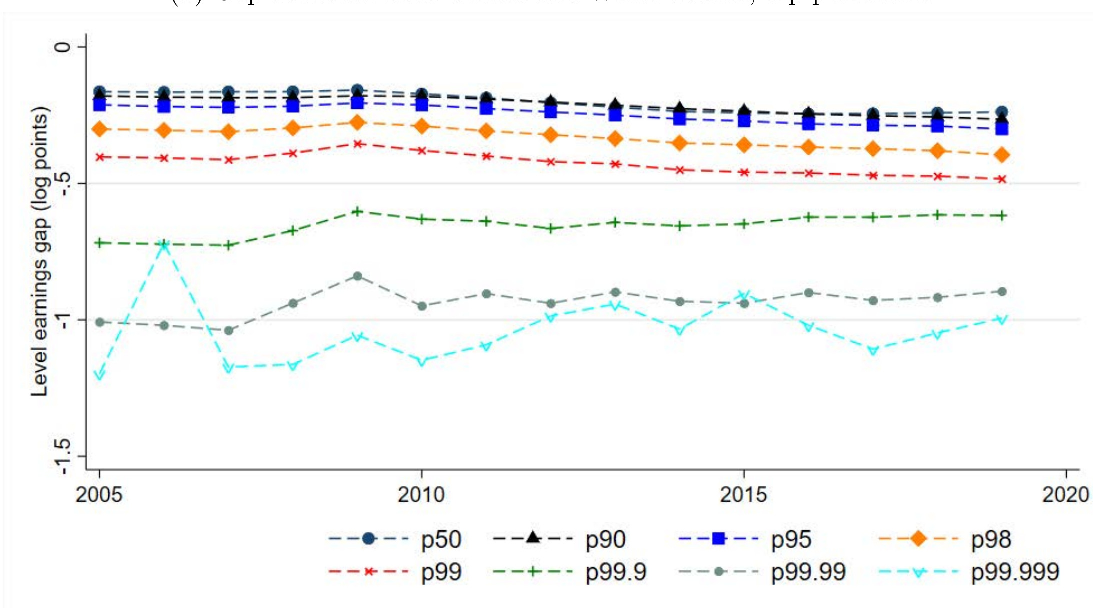


Figure A.5: Gap between Black and White women

Source: IDDA and authors' calculations.
Note: Each panel plots the earnings gap between prime-age Black women and White women, in log points. Includes workers aged 25-54 with earnings at least equivalent to working 20 hours a week for 13 weeks at the federal minimum wage. Ethnicity is non-Hispanic unless otherwise specified. Release authorization CBDRB-FY23-0277.

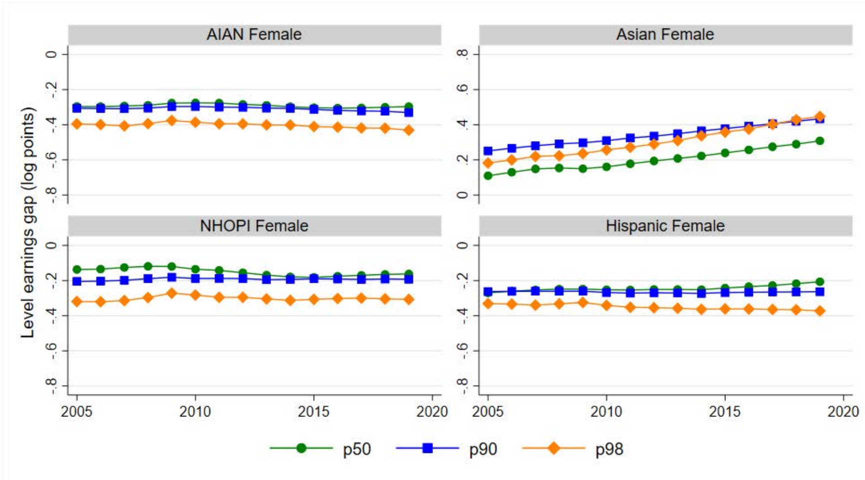


Figure A.6: Gap between non-White and White women

Source: IDDA and authors' calculations.
Note: Each panel plots the earnings gap between prime-age non-White women and White women, in log points. Includes workers aged 25-54 with earnings at least equivalent to working 20 hours a week for 13 weeks at the federal minimum wage. Ethnicity is non-Hispanic unless otherwise specified. Release authorization CBDRB-FY23-0277.

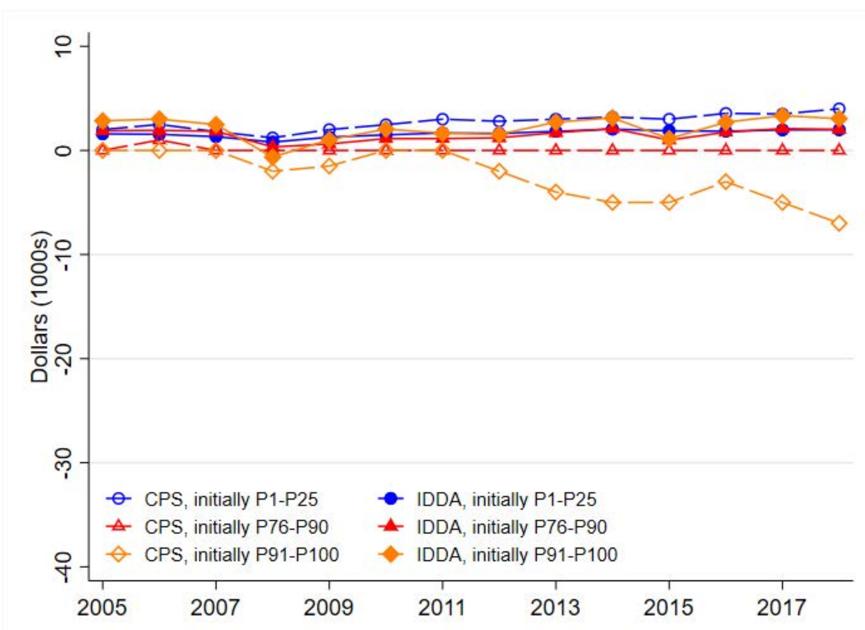


Figure A.7: Median wage and salary income growth by base year income, excluding CPS topcodes and imputed values

Source: CPS, IDDA and authors' calculations.
Note: Values are in nominal dollars. Growth measures are computed at the individual level. Release authorization CBDRB-FY23-0277.

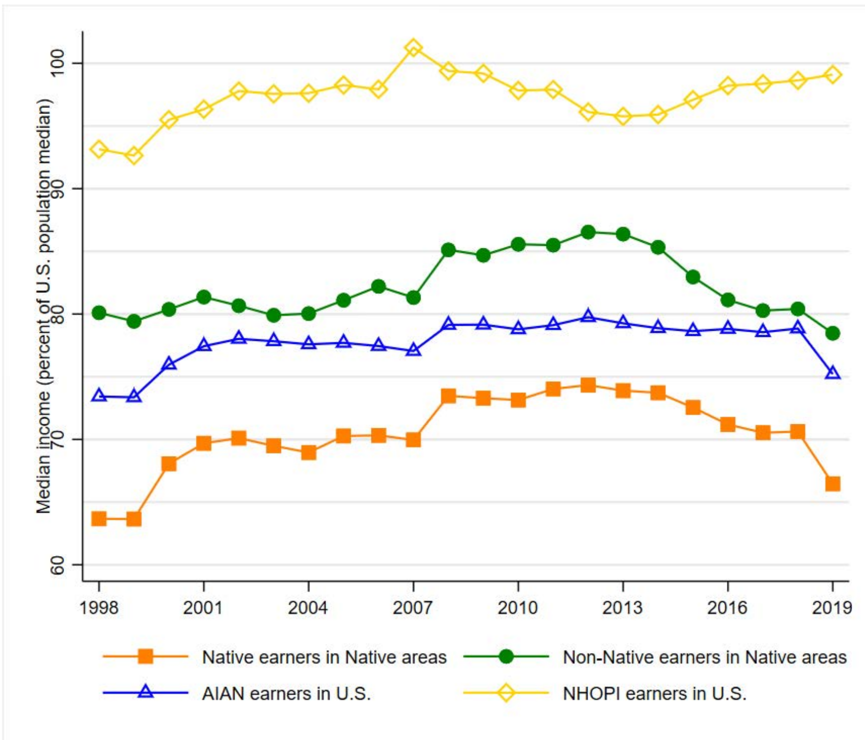


Figure A.8: Median household income in Native Areas, relative to U.S. population

Source: IDDA and authors' calculations.
Note: Each point plots relative median income in the given race and ethnicity group, expressed as a percentage of the U.S. population median. Household income in IDDA is summed across all 1040 forms filed at a common address, and the household-level total is assigned to each adult resident. This provides a measure of resources available to individuals in different demographic groups. The groups of all American Indian or Alaska Native earners and all Native Hawaiian or other Pacific Islander earners include some individuals living in Native areas who identify only as single-race, non-Hispanic AIAN or NHOPI. Release authorizations CBDRB-FY23-0373 and CBDRB-FY23-0277.

Appendix B

Dissecting IDDA vs. CPS Income Differences[1]

May 15, 2024

1 Introduction

In section 3 of the paper, we showed that income inequality trends differ between IDDA and the CPS. For instance, income changes over time and across states are flatter in the CPS, compared with IDDA. There are several reasons IDDA and CPS could give different patterns: from noise in survey income measures to "non-classical" sources of differences such as sample composition and selection, income definition and misclassification, or survey data biases due to imputation, proxy responses, or misreporting.

We compiled a supplementary dataset to further compare income distributions in IDDA with those in the restricted-use Current Population Survey Annual Social and Economic Supplement (CPS ASEC), a standard source for income measurement in the U.S. The IDDA CPS Supplement dataset contains percentiles of income in the CPS disaggregated by race/ethnicity, sex, and place of birth (foreign-born or U.S.-born) for a subset of tax years, as well as analysis of a linked CPS-IRS sample. These supplementary statistics help account for the differences between the IDDA statistics and their counterparts measured in the CPS.

Related literature The literature suggests pure classical errors—that is, random measurement errors in the survey data that are orthogonal to the true income—do not drive the divergence between survey and administrative income measures. Bollinger et al. (2019) link the restricted CPS ASEC data to SSA W-2 records and find that nonresponse is higher in both tails of the earnings distribution and varies across demographic groups. Differences in nonresponse rates tend to bias within-group income inequality downward and also affect estimates of inequality across

[1]The opinions and conclusions expressed here are those of the authors and should not be interpreted as reflecting the views of the Federal Reserve Board of Governors, the Federal Reserve Bank of Minneapolis, or any other person associated with the Federal Reserve System. Any opinions and conclusions expressed herein are those of the authors and do not represent the views of the U.S. Census Bureau. The Census Bureau has ensured appropriate access and use of confidential data and has reviewed these results for disclosure avoidance protection (Project 7511151; Disclosure Authorization Numbers CBDRB-FY23-0277, CBDRB-FY23-0373, CBDRB-FY23-CES014-019, CBDRB-FY23-CES014-016, and CBDRB-FY24-0131.)

groups on both ends of the income distribution.[2] Kim and Tamborini (2012) link the Survey of Income and Program Participation (SIPP) respondents to SSA W-2 records and find evidence of income overreporting by low earners and underreporting by top earners. This type of non-classical error leads to a downward bias in within-group earnings inequality in the SIPP survey. They also found that Black-White earnings disparities are misestimated in the SIPP because of both larger overreporting at the bottom and more underreporting at the top among Black respondents, compared with White respondents. Gideon et al. (2022) show that income reporting patterns in the CPS differ within and across race, gender, and education groups, and these differences influence inequality estimates. Murray-Close and Heggeness (2019) document that a woman's earnings are underreported in the CPS by her male partner when he earns just less than her. Tamborini and Kim (2013) also document a proxy-respondent downward bias against single women in the SIPP.

Using the restricted-use CPS ASEC data, we explore various non-classical sources of differences in our IDDA setting to help interpret the differences between IDDA and the CPS for IDDA potential users. Consistent with the granular theme of the paper, we highlight how IDDA and CPS incomes diverge across race/ethnicity groups, for different income concepts, and along the income distribution. For instance, we note that racial differences in the fraction of non-zero W-2 earners with zero CPS earnings account for most of the racial differences in overreporting by individuals with low earnings.

2 IDDA–CPS Income Comparison Approach

The restricted-use CPS microdata do not contain ranked proximity swaps of top incomes and feature higher topcodes than the public-use microdata. Hence, measured incomes in the survey data should be closer to those in the administrative data than they are to incomes from the public-use data.[3] We can link the primary samples of 1040 and W-2 records underlying IDDA to the restricted-use CPS data using PVS-assigned identifiers (PIKs).

[2] Hokayem et al. (2015) also document that a higher nonresponses rate among low income households leads to lower estimates of poverty rate in the CPS. See Meyer et al. (2015) on transfer income underreporting in surveys.

[3] As of data year 2019, the primary component of person-level wage and salary income was topcoded at just under $10 million in the internal files, compared with a proximity swap threshold of $360,000 in the public-use data. In addition, from data year 2010 onward, the public-use files (but not the internal files) use a ranked proximity swapping procedure to assign income values above the topcode. See topcodes documentation in Flood et al. (2023) for details.

Income samples We contrast income measures across four main samples: (a) the unlinked IDDA sample of incomes, (b) the unlinked, restricted-use CPS sample of incomes, (c) the linked IDDA sample of incomes for respondents or households present in both the restricted-use CPS and the primary IDDA sample, and (d) the linked CPS sample of incomes for respondents or households present in both the restricted-use CPS and the primary IDDA. To construct the linked datasets, we merge CPS ASEC records from a given survey year to the final IDDA W-2 and 1040 samples from the corresponding tax year via the PIK (the relevant tax year for CPS ASEC earnings data is the one before the survey collection date). The unlinked, restricted-use CPS samples are defined in the same way as in the public-use CPS analysis. At the individual level, the unlinked sample includes ASEC respondents aged at least 16 who report positive wage and salary income. At the household level, the unlinked sample includes all ASEC respondents aged at least 16, including those who report zero household income. This is because the 1040 records underlying IDDA include returns with zero adjusted gross income. The linked samples inherit IDDA sample selection criteria. (See section 2 in the main paper for the construction of the IDDA samples.)

Income variables Next, we harmonize the income concepts across sources and the key variables we leverage to explore non-classical errors.[4]

Table B.1 describes the income variables used in the CPS and summarizes relevant differences from the tax measures used in IDDA. The individual-level earnings concepts and household wage and salary earnings align closely, but the household total income measures differ in a number of meaningful ways, highlighted in the right column.

Comparison flags We leverage various flags to inspect potential sources of divergence between IDDA and CPS incomes across race/ethnicity groups and along the income distribution. Imputation flags from the restricted-use CPS microdata allow us to assess how earnings nonresponse and survey data treatment of it contribute to the differences between IDDA and CPS incomes. At the individual level, we code an income concept as imputed for a respondent if any component of the income variable was imputed. At the household level, we code an income concept as imputed if it was imputed for the household member with the largest value for that income variable. For

[4]See Roemer (2000) for a comparison of incomes in the CPS and national accounts.

individual earners, we also use a flag for proxy-provided income responses to explore the role of proxy-induced differences between incomes in the CPS and tax data. To explore the role of income misclassification, we use a flag from the tax data indicating whether an individual received a Form 1099-MISC, a form typically received by self-employed workers.[5] Finally, we use the discrepancy between household size in the CPS and in IDDA to study whether the aggregation of tax units into households using Census address identifiers influences earnings measurement.

Table B.1: Income concepts in IDDA and the Current Population Survey

CPS Income Concept	Description	Types of Income Included	IDDA Income Concept	Major Differences
WSAL_VAL	Individual wage/salary earnings	Earnings from longest job if received wage/salary income in longest job + total wage or salary earnings from additional jobs. Includes tips, bonuses. Excludes self-employment, except if respondent owns an incorporated business and receives wages from it.	Individual-W2, wage compensation (WC) or total compensation (TC)	Neither the CPS nor IDDA wage income concept includes self-employment income. However, research has shown some CPS respondents misclassify self-employment income as wage income. TC includes elective deferrals reported in Box 12 of form W-2. In this section, individual earnings comparisons are based on WC.
HWSVAL	Household wage/salary income	Total of WSAL_VAL aggregated across all earners in a household	Household-1040, wage/salary income (WS)	See above row. Addresses may not align between the CPS and IRS data sources, causing household assignment to differ across the two sources for a given individual.
HTOTVAL	Total household income	Total income aggregated across all earners in a household. This includes wage and salary income and self-employment income, as well as non-wage income sources: *Social Security, SSI income, public assistance and welfare, disability income,* interest and dividends, rental income, veterans' benefits, *workers' compensation,* survivor's income, alimony, *child support payments,* distributions from pension or private retirement accounts, and unemployment compensation.	Household-1040, Adjusted gross income (GI)	CPS measure includes some types of nontaxable or partially taxable income that are excluded in IDDA (in italics). The CPS measure excludes above-the-line deductions on Form 1040, for example deductions from health savings accounts and student loan interest payments, which are subtracted from household AGI. The CPS measure excludes capital gains, which are included in household AGI.

[5]If individuals doing non-employee work receive an information return, it is most likely Form 1099-MISC. However, not all income earned by individuals doing non-employee work has an associated information return (Abraham et al., 2019). We do not observe the total earnings reported on 1099 forms, only whether an individual received one.

3 Individual Earnings Differences

Differences across unlinked data sources The analysis in section 3 of the main paper compared changes in distributional statistics over the full IDDA data period (1998-2018 for household income measures and 2005-2018 for individual earnings measures). Before delving into the sources of earnings differences, we compare earnings levels along the distribution for the overall sample and three selected race/ethnicity groups (Hispanic, non-Hispanic White, and non-Hispanic Black earners) in the CPS Annual Social and Economic Supplement and in IDDA. We focus on these groups to illustrate where and why results from IDDA might diverge from those in other income data sources, and to show that these differences vary across race and ethnicity even in relatively large samples.

Figure B.1 shows the 10th through 98th percentiles of individual earnings in 2012 (though similar patterns occur in 2005 and 2019). For all three groups, percentiles of earnings measured in the Current Population Survey are higher than in IDDA. In percentage terms, these differences are quite large at the bottom of the distribution (the 10th percentile of earnings in the CPS is close to double that in IDDA, and more for Black earners) but still meaningful at higher percentiles. However, magnitudes differ across the three race/ethnicity groups. The difference in earnings measured in the CPS and IDDA is higher for Black earners than for White earners at all percentiles. For Black earners, CPS earnings are around 30 percent higher than IDDA earnings at the median and 13 percent higher at the 98th percentile. For White earners, the difference falls from 17 percent at the median to 1 percent at the 98th percentile. As a result, relative to IDDA, the CPS understates the Black-White earnings gap, particularly in the tails of the distribution. Earnings percentiles measured in the CPS and IDDA are somewhat closer together for Hispanic earners.

Figure B.1 also suggests that measures of within-group inequality vary between the CPS and IDDA. For White and Black earners, both the 90/50 and 90/10 percentile ratios are lower in the CPS than in IDDA, since the difference in income values between the CPS and IDDA is larger in proportionate terms at the bottom and median than at the top. For Hispanic earners, the 90/10 ratio is substantially lower in the CPS than in IDDA, but not the 90/50 ratio.

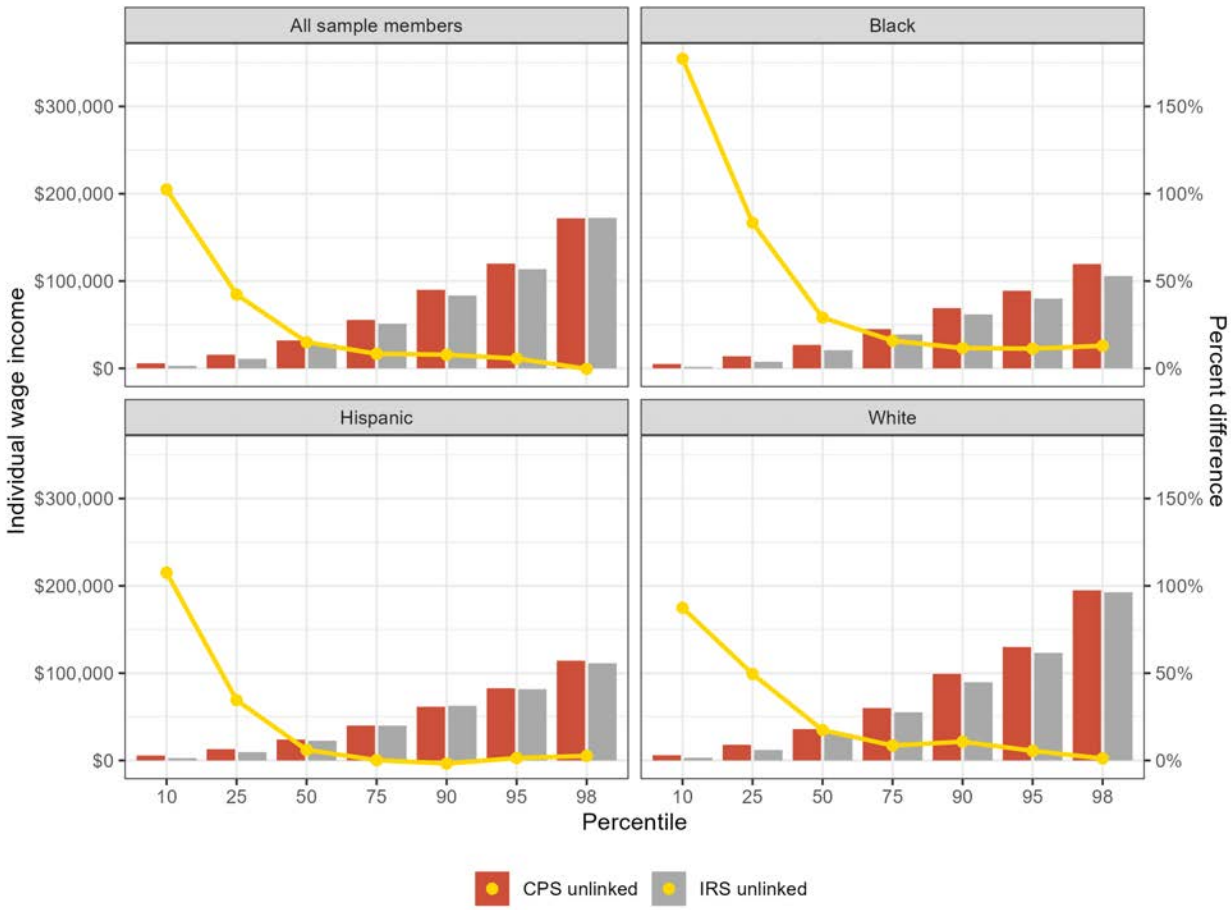


Figure B.1: Annual earnings in the CPS and in IDDA, by race and ethnicity, in 2012

Source: IDDA and Current Population Survey.
Note: Figure charts selected percentiles of the individual annual earnings distribution by race and ethnicity in 2012. Release authorizations CBDRB-FY23-0277 and CBDRB-FY23-0373.

Differences using linked samples Figure B.2 shows how these patterns change when we compare earnings measured in the CPS and administrative tax data for the same underlying sample. Among individuals we see in the W-2 data, does the distribution of CPS-reported earnings still look different from the distribution of earnings in the tax data? In the matched CPS-IDDA sample, we include respondents who do not report positive wage income in the CPS. This leaves open the possibility that both earnings and employment margin reporting differences influence distributional measures, including differences driven by earnings nonresponse in the CPS.

Restricting ourselves to the linked CPS-IDDA sample attenuates many of the differences observed in Figure B.1. At the bottom of the distribution, the large positive differences between earnings percentiles in the CPS and in IDDA become negative and much smaller in magnitude. In fact, the 10th percentile of CPS-reported earnings in the linked sample is zero for both Black and Hispanic earners and very small for White earners. In other words, at least 10 percent of Black and Hispanic earners in the linked sample do not report wage earnings to the CPS despite having received a W-2 showing positive wage compensation in 2019.[6] This employment margin difference suggests the IDDA W-2 data may be more likely than survey sources, to capture very small earnings values, such as earnings for very part-time workers or from short-term jobs, of note to data users.

At the highest earnings percentiles, CPS-defined earnings measures again fall below those based on IDDA. Yet, splitting the sample by race/ethnicity shows this pattern is driven by White respondents – and it is limited to percentiles above the 95th, which are substantially higher for White earners than for other groups. So, Figure B.1 is consistent with racial differences in reporting patterns that are driven by differences in income levels across groups. These differences influence inequality measures across groups but primarily at the top of the distribution or as a result of the employment margin, in line with Chenevert et al. (2015), who find that replacing survey-reported earnings with administrative earnings has little impact on average Black-White earnings gaps.[7]

Respondent-level earnings differences and determinants Both Figures B.1 and B.2 report sample-level differences in earnings and inequality measurement between the CPS and IDDA.

[6] Chenevert et al. (2015) similarly find that 9 percent of respondents with positive administrative earnings had no survey-reported earnings in a linked SIPP-DER dataset.

[7] Other authors, including Kim and Tamborini (2012) and Gideon et al. (2022), find more salient differences across race/ethnicity in linked survey-administrative data, but look at more granular demographic groups than we include here.

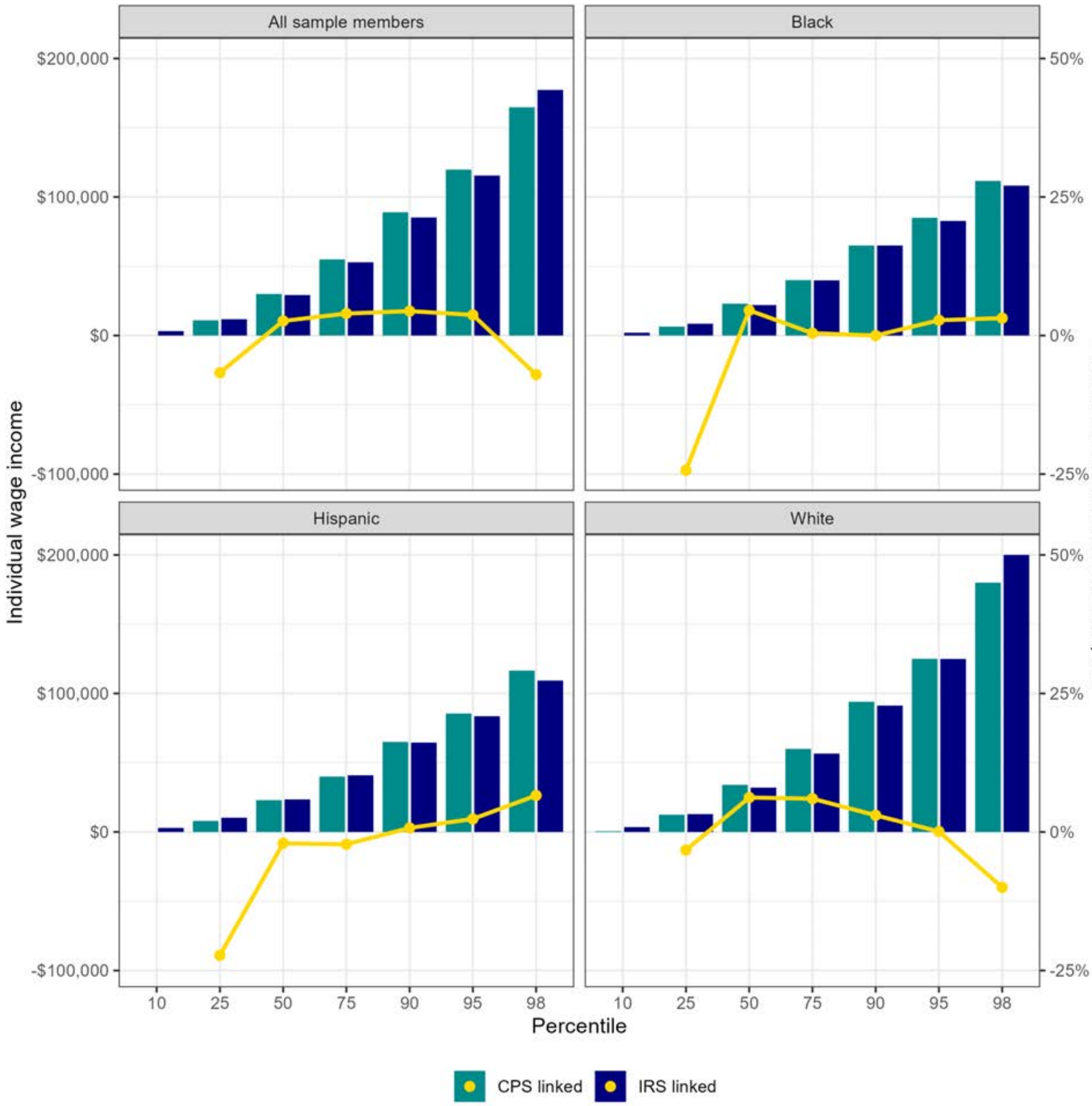


Figure B.2: Distribution of earnings in matched CPS-IDDA sample, by race and ethnicity

Source: IDDA and Current Population Survey.
Note: Figure charts selected percentiles of the individual annual earnings distribution by race and ethnicity in 2012. The linked sample includes CPS ASEC respondents aged 16 or over who can be matched to the IDDA W-2 sample via the PIK, which restricts the sample to individuals with positive wage compensation recorded on Form W-2. Release authorization CBDRB-FY23-0373.

Another approach is to assess individual-level differences in earnings reported to the CPS and in the tax data for earners in the matched sample. We summarize individual-level reporting differences within quantiles of the W-2 earnings distribution, and further split these between self-reported, proxy reported, and imputed earnings values. Additionally, we consider earners with a 1099-MISC information return (which identifies likely self-employed workers).

The results are shown in Figure B.3. The boxplots show the 25th percentile, median, 75th percentile, and mean earnings difference between the CPS and W-2 records, for individuals in the top and bottom quantiles of the W-2 earnings distribution. The comparison includes both earnings and employment margin differences (an individual with zero CPS-reported earnings and \$$x$ in W-2 earnings receives an earnings difference value of –\$$x$). Quantiles of the W-2 distribution are defined in the overall linked sample, across demographic groups.

Individual-level differences in CPS-reported earnings and W-2 earnings are highest in absolute terms at the top of the distribution, consistent with previous findings linking the CPS and SIPP to administrative records (Kim and Tamborini, 2012; Bollinger et al., 2019). The median earnings difference among individuals in the top 10 percent of the W-2 earnings distribution was just under –\$7,000 (i.e., the earner with the median reporting difference reported \$7,000 less in income to the CPS than is recorded on their W-2 record). The mean was close to \$40,000, suggesting a small number of large underreports in the CPS relative to the W-2 data. Among those in the bottom quartile of W-2 earnings, the median earnings difference was close to zero, but the mean was nearly \$5,000, a meaningful gap—the 25th percentile of individual W-2 earnings in the linked sample was \$11,790. These patterns may reflect social desirability bias (respondents may report an income they perceive as closer to average), differential nonresponse, participation in informal labor market activities, or income misclassification (Kim and Tamborini, 2012; Abraham et al., 2021; Imboden et al., 2023). They could also include misreporting of earnings by employers (Gideon et al., 2022).

Within quantiles of the overall W-2 earnings distribution, the IQR of individual-level earnings differences were largely similar for Black, Hispanic, and White respondents. The median earnings difference among top White earners was somewhat smaller than the one for other groups, but the mean was much larger: White earners appear overrepresented among large CPS-underreporters at the top of the distribution.

Breaking out our comparison by response status, we note that reporting differences were larger among high earners whose CPS earnings were given by a proxy respondent.[8] Earners with a 1099-MISC information return also had greater mismatch. At the bottom of the distribution, this likely reflects misclassification of self-employment income as wage income, which research has documented in the CPS and is especially relevant for gig workers (Abraham et al., 2019, 2021). The largest systematic mismatch occurs for individuals whose wage income was imputed in the CPS. This result bears out the finding that earnings nonresponse is nonrandom in the CPS ASEC (Bollinger et al., 2019). Overall, very high and very low earnings are not well observed in the CPS even without topcoding, and this problem is worse for individuals who do not respond to earnings items or have a more complicated mix of income sources. This has been shown previously in linked CPS-administrative data, and it is true for the IDDA samples as well. An implication for data users is that the CPS tends to give lower readings of inequality both within and across groups than the IDDA W-2 sample when those measures rely on the tails of the distribution. Similarly, small nominal changes in low earnings percentiles in IDDA can substantially move percentile ratio measures.

4 Household Income Differences

Household income concepts in IDDA provide measures of total resources available to individuals sharing a common residence. Understanding how these income concepts and household aggregation methods may differ from other sources can help users determine the best applications of the IDDA data to their research question. For instance, household income measures in IDDA are not well suited to studying poverty, as they do not contain transfers or other after-tax income sources.

Here, we compare the distribution of household income measures in the linked CPS-IDDA 1040 sample. This restricts the ASEC sample to individuals who are listed as a primary or secondary filer on a Form 1040 filed for the year 2012. The distribution of household income is somewhat higher in the linked sample than in the unlinked CPS, in line with this restriction.

[8] Close to half of ASEC earnings reports are given by proxy respondents, and more than a quarter of earnings reports are imputed (Bollinger et al., 2019).

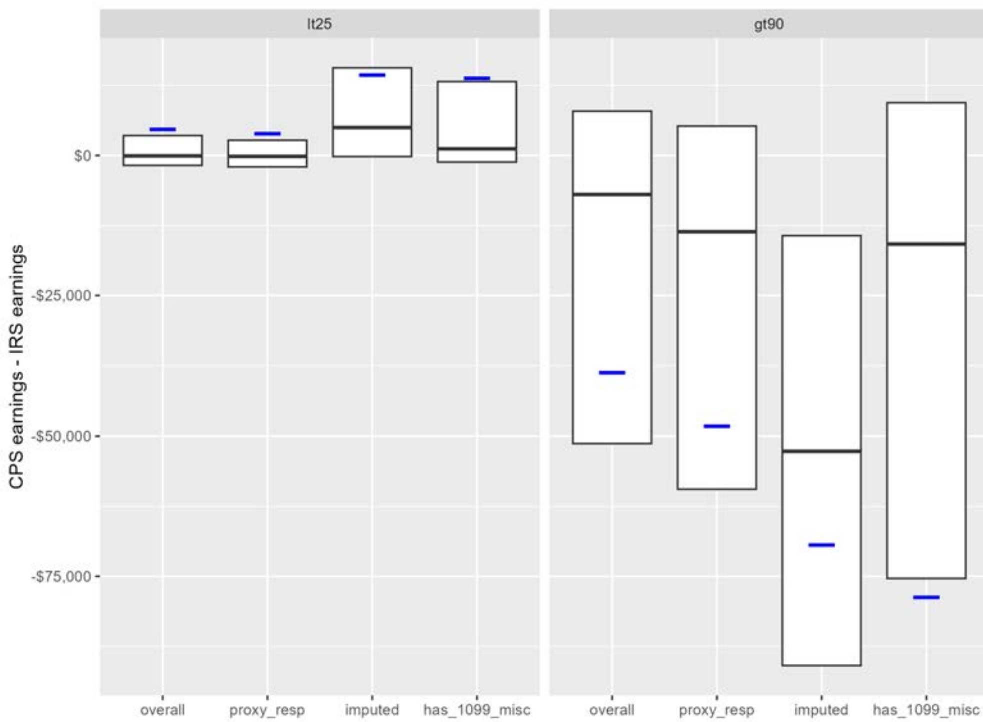


Figure B.3: Summary of earnings differences in top 10 percent and bottom 25 percent of W-2 earnings

Source: IDDA and Current Population Survey.
Note: Boxplots show the 25th, 50th, and 75th percentiles of earnings differences between individual wage earnings reported in the CPS and IDDA W-2 data. These are reported for respondents in the bottom 25 percent of individual earnings (left) or the top 10 percent (right), defined using W-2 wage compensation in the linked sample. On the horizontal axis at the bottom of the figure, "proxy_resp" indicates whether CPS earnings were given by a proxy respondent; "imputed" flags respondents whose CPS wage earnings were imputed; "has_1099_misc" indicates whether the respondent received a 1099-MISC information return. The blue bars show mean earnings differences for each group. Release authorization CBDRB-FY23-0373.

Differences using linked samples Percentiles of household wage and salary income in the CPS and IDDA are shown in Figure B.4. As with individual earnings, the overall pattern is an inverted-U shape: percentiles of income as measured in the CPS are lower than those in IDDA in the tails of the distribution, and similar to those in IDDA around the median (shown in the top left panel). The other three panels show that differences at the highest-income percentiles are more pronounced for White respondents, while those at lower percentiles are more pronounced for Black and Hispanic respondents. This influences relative income measures only slightly at the top: for example, at the 98th percentile, the Black-White income ratio is 66 percent using CPS household wage and salary income and 63 percent using IDDA. The effect is larger in ratio terms at the 25th percentile.[9] Still, we conclude that along much of the distribution, percentiles of household wage and salary income are closely aligned in the linked sample.[10]

In both the CPS and IDDA, household wage and salary income is the sum of earnings for individuals sharing a common address. Both Figure B.2 and Figure B.4 show relatively small differences between the CPS and IDDA, and similar patterns across race/ethnicity. However, percentiles of household wage and salary income are lower relative to IDDA than percentiles of individual earnings, particularly in the middle of the distribution. This could stem from a number of factors. Individuals who over- or underreport income in the CPS, relative to IDDA, could reside with earners who show the same, opposite, or no reporting difference. Such sorting patterns within households could vary across the income distribution and/or by race and ethnicity. It's also possible that the aggregation of income across 1040 forms captures different earners than the aggregation of incomes across workers in the CPS. Table B.2 includes a more detailed description of households in the CPS and IDDA, and finds a high rate of overlap between household constructs in the linked sample.

On the other hand, we do find notable differences in measures of total household income. These patterns are consistent with differences in the types of income captured by household AGI in

[9] Yet, respondent-level differences in the linked sample show that low-income Black and Hispanic filers do not appear more likely than low-income White respondents to underreport household wage and salary income in the CPS, relative to IDDA (see Figure B.9).

[10] This analysis includes incomes reported on 1040 forms filed for the tax year 2012. One way to explore whether patterns change as the universe of filers changes is to consider 2019, as many households with low or zero income filed taxes for that year to receive Covid-19 stimulus payments. Figure B.8 shows that percentiles of household wage/salary income are higher in the CPS, relative to IDDA in the linked sample in that year – the distribution of income in IDDA is pushed to the right as a result of filing changes. The effect is strongest at low percentiles, creating a downward sloping trend in CPS-IDDA differences along the distribution, as opposed to an inverted U.

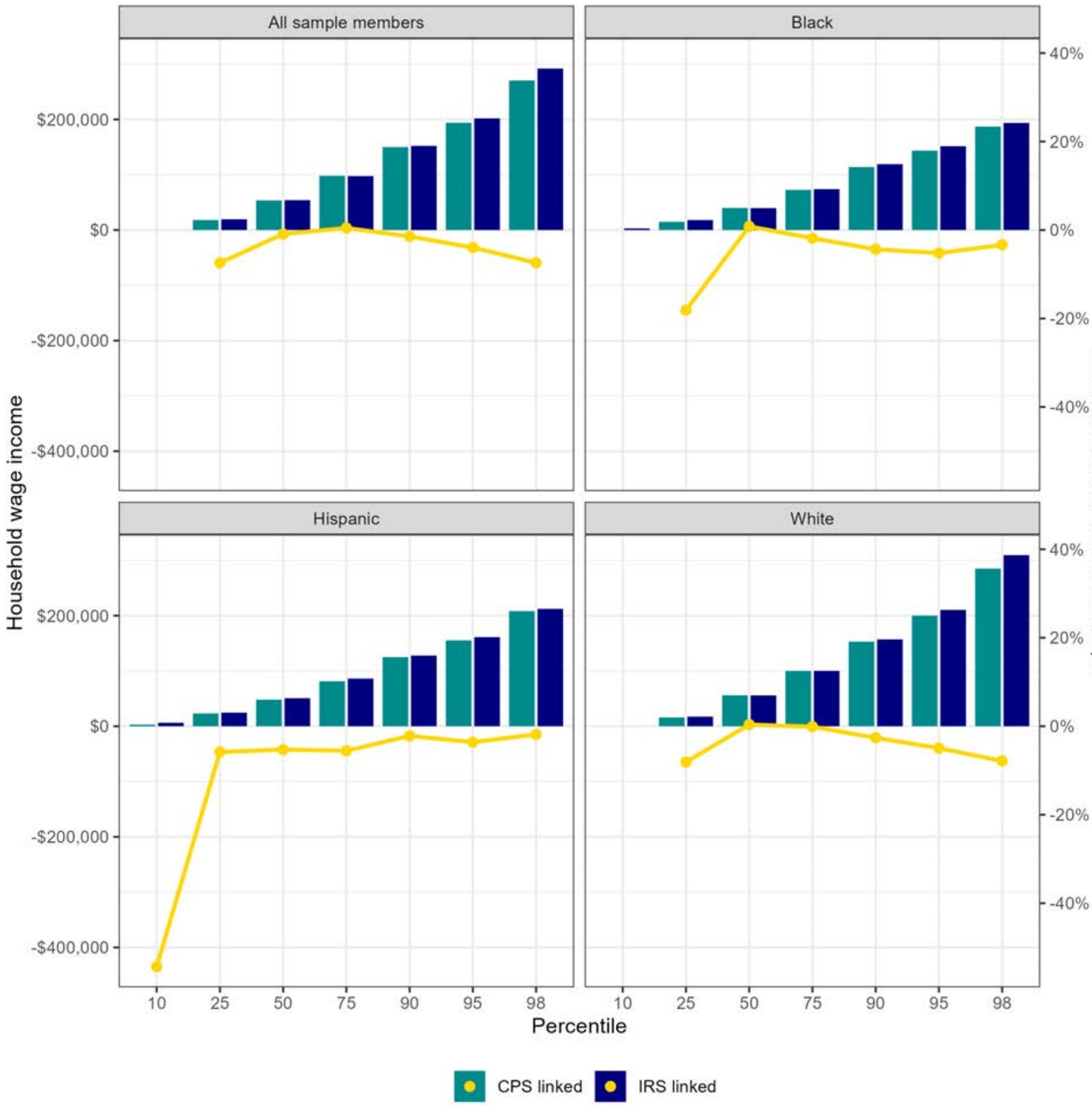


Figure B.4: Distribution of household wage and salary income in matched CPS-IDDA sample, by race and ethnicity

Source: IDDA and Current Population Survey.
Note: Figure charts selected percentiles of the distribution of household wage and salary income by race and ethnicity in 2012. The linked sample includes CPS ASEC respondents aged 16 or over who can be matched to the IDDA 1040 sample via the PIK, which restricts it to individuals listed as a primary or secondary filer on a Form 1040 filed for tax year 2012. Release authorization CBDRB-FY23-0373.

IDDA and the closest CPS variable, but they vary across race/ethnicity. This analysis is shown in Figure B.5. For White filers and in the overall linked sample, the distribution of CPS total household income is compressed relative to the distribution of household AGI: CPS incomes are both larger than IDDA AGI at the bottom and much smaller than IDDA AGI at the top. For Black and Hispanic respondents, this pattern is much less stark. For Hispanic respondents in particular, percentiles of income measured in the CPS hover at about 5 percent lower than IDDA at the median and above. Therefore, the CPS documents smaller income gaps between Black and Hispanic respondents and White respondents than IDDA does at the top of the distribution.

Racial differences in the measurement of total household income may reflect the role of capital gains, a growing source of top incomes that has disproportionately accrued to White households and is not captured in the CPS total household income variable (Derenoncourt et al., 2023). At the bottom of the distribution, the CPS household income concept includes sources of transfer income that are nontaxable and so are not captured in IDDA. We are not able to disentangle these differences in variable definition from reporting patterns in non-labor income sources (such as transfer or retirement income, as in Meyer and Mittag (2019) and Bee and Mitchell (2017)), since we cannot isolate individual components of non-wage income in the tax data.

Household-level earnings differences and determinants Finally, we look at household-level differences between household wage and salary income values observed in the CPS and the 1040-derived tax data for individual respondents in the matched sample. We explore the role of household characteristics at the top and at the bottom of the earnings distribution. We consider the following household variables: whether the household contains any dependents, whether the highest earner's household wage and salary income was imputed in the CPS, and whether the highest earner in the household received a form 1099-MISC. We also consider whether household size in the CPS exactly matches the size of the MAFID-based household in the IDDA sample. We report our findings in Figure B.6.

At the bottom of the distribution, we find that CPS-reported wage and salary income is higher than household WSI measured in the tax sample for most respondents. This is especially true for households with dependents, with a 1099-MISC, and with imputed wage and salary income. In contrast, at the top of the distribution, CPS wage and salary income is less than household WSI, as

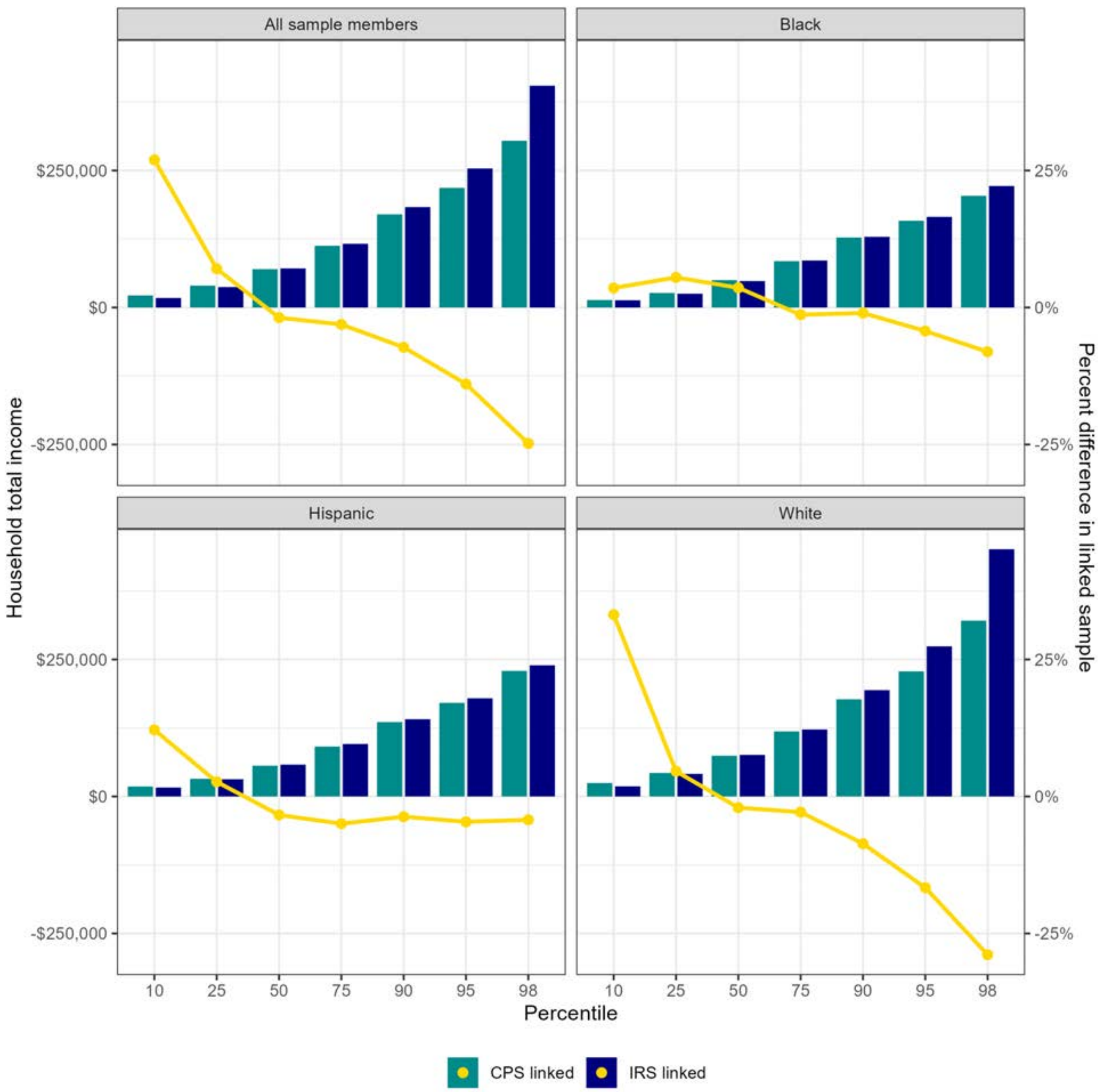


Figure B.5: Distribution of total household income in matched CPS-IDDA sample, by race and ethnicity

Source: IDDA and Current Population Survey.
Note: Figure charts selected percentiles of the distribution of total household income by race and ethnicity in 2019. The linked sample includes CPS ASEC respondents aged 16 or over who can be matched to the IDDA 1040 sample via the PIK, which restricts to individuals listed as a primary or secondary filer on a Form 1040 filed for tax year 2012. Release authorization CBDRB-FY23-0373.

expected. Households whose size matches exactly in the CPS data and in the IRS data have slightly less mismatch, and households with imputed wage and salary income have much more mismatched incomes.

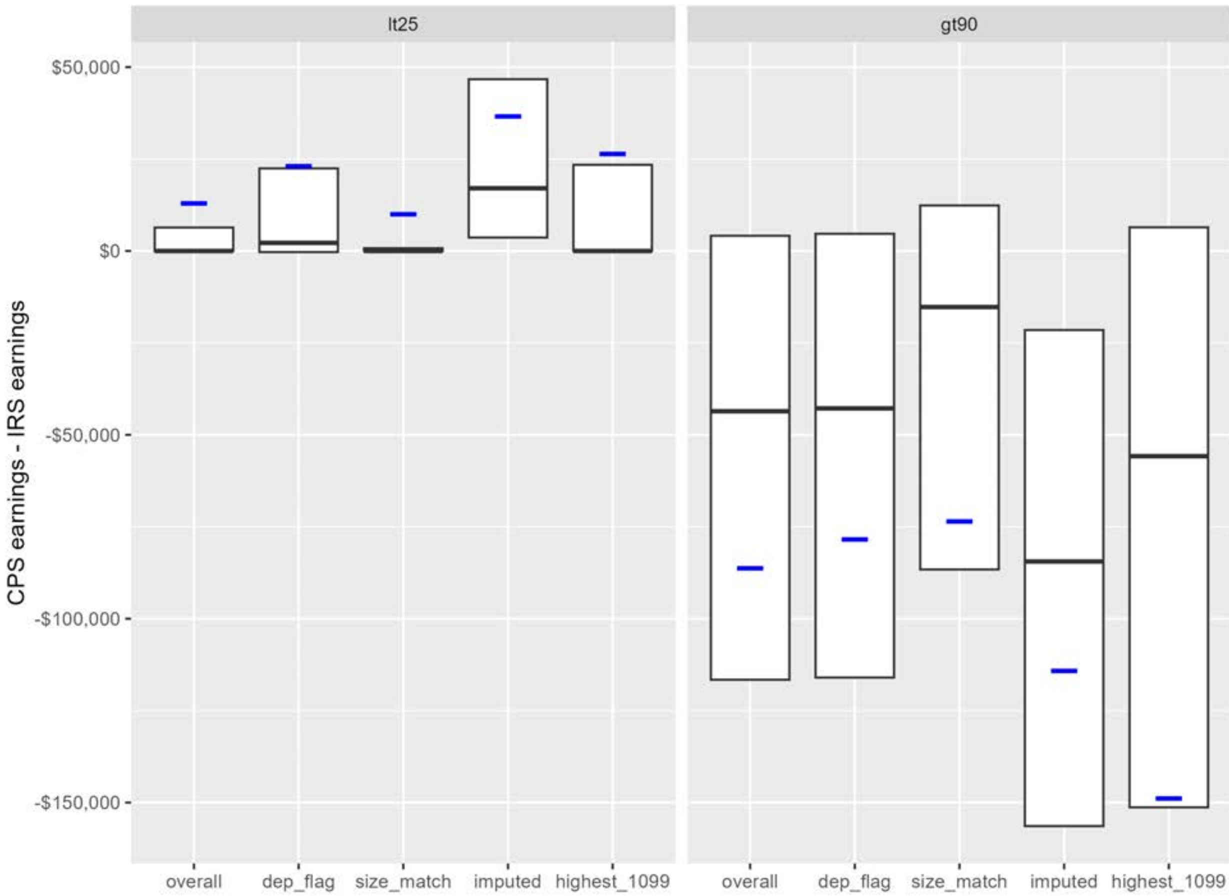


Figure B.6: Household earnings differences by household characteristics

Source: IDDA and Current Population Survey.
Note: Boxplots show the 25th, 50th, and 75th percentiles of earnings differences between household wage and salary income reported in the CPS and IDDA 1040 data. These are reported for respondents in the bottom 25 percent of household wage and salary income (left) or the top 10 percent (right), defined using the 1040 household WSI measure in the linked sample. On the horizontal axis at the bottom of the figure, "dep_flag" indicates respondents whose IDDA household includes at least one dependent; "size_match" indicates an exact match between household size constructed in the CPS and IDDA; "imputed" flags whether the highest wage/salary earner in the CPS household had any imputed income values; and "highest_1099" indicates whether the highest total earner in the CPS household had a 1099-MISC information return. The blue bars show mean earnings differences for each group. Release authorization CBDRB-FY23-0373.

4.1 Address-Based Households in IDDA

Table B.2 shows how the address identifier ("MAFID") used to construct household incomes in IDDA maps onto households in the Current Population Survey, using the tax year 2012 as an example. The first column compares the rate of overlap between MAFIDs and households in the CPS ASEC: A CPS household is considered a "match" to its IDDA counterpart if all the household members in the CPS have the same value of MAFID in the IDDA sample and if all the members of the IDDA MAFID that show up in the CPS data are part of the same CPS household. This rate is high, at least 90 percent for all demographic groups. However, it does not rule out situations where some members of a CPS household are not represented in the IDDA samples.

Table B.2: Households and addresses in the CPS and IDDA

Group	MAFID overlap rate with CPS households	Mean CPS household size	Mean IDDA household size	Exact MAFID household size match
All	94%	2.87	3.12	63%
Hispanic	90%	3.5	3.9	47%
AIAN	91%	3.1	3.4	52%
Asian	94%	3.3	3.6	58%
Black	90%	3	3.3	49%
NHOPI	91%	3.7	4	52%
White	95%	2.7	3	68%
Foreign-born	93%	3.3	3.7	54%
U.S.-born	94%	2.8	3.1	64%

Note: Table shows characteristics of households in the linked CPS-IDDA 1040 sample, using tax year 2012 as an example. In IDDA, household size is defined as the total number of primary and secondary filers and dependents reported on all 1040 forms filed at a common address (MAFID). The household "overlap rate" gives the probability that, within the linked sample, CPS and IDDA households match 1:1 (all observed CPS household members are linked to the same MAFID, and all observed members of the MAFID are part of the same CPS household). Release authorization CBDRB-FY23-0373.

The second and third columns show that, on average, household size is slightly larger in IDDA than the CPS, possibly because some tax filers claim dependents who do not physically reside with them (for example, students or elderly family members). However, the relative differences in mean household size across demographic groups is preserved between both sources. Finally, column 4 suggests that the CPS and IRS household concepts are less tightly aligned for individuals who are non-White or Foreign born: even though the difference in mean household size between the CPS and IRS data is not particularly large for these groups, they are less likely to reside in a CPS household that has the exact number of members associated with their value of MAFID in the IDDA samples.

5 Conclusion

Studies using linked survey and administrative data have explored how income reporting patterns in surveys might vary across groups or along the income distribution. We apply these insights to IDDA to better understand the sources of divergence from public-use data documented in the paper. Overall, wage and salary-derived income measures align well between the CPS and IDDA at both the individual and household level. Consistent with prior literature, we find some "trouble in the tails" (Bollinger et al., 2019).

At high percentiles, relative to IDDA, the CPS tends to understate earnings levels and measures of earnings gaps across race/ethnicity groups. This pattern is expected and matched by respondent-level differences in earnings reported to the CPS and in the tax data. However, we add that it is driven primarily by the top of the White earnings distribution in our data setting. At low percentiles, we find that differences between the CPS and IDDA are sensitive to the fraction of non-zero W-2 earners with zero CPS earnings, especially for Black and Hispanic respondents.

Finally, we suggest that differences in the types of non-wage income captured in the CPS and in IDDA are meaningful for understanding discrepancies in total household income measures, such as those reported in Table 6 of the main paper.

6 Additional Figures

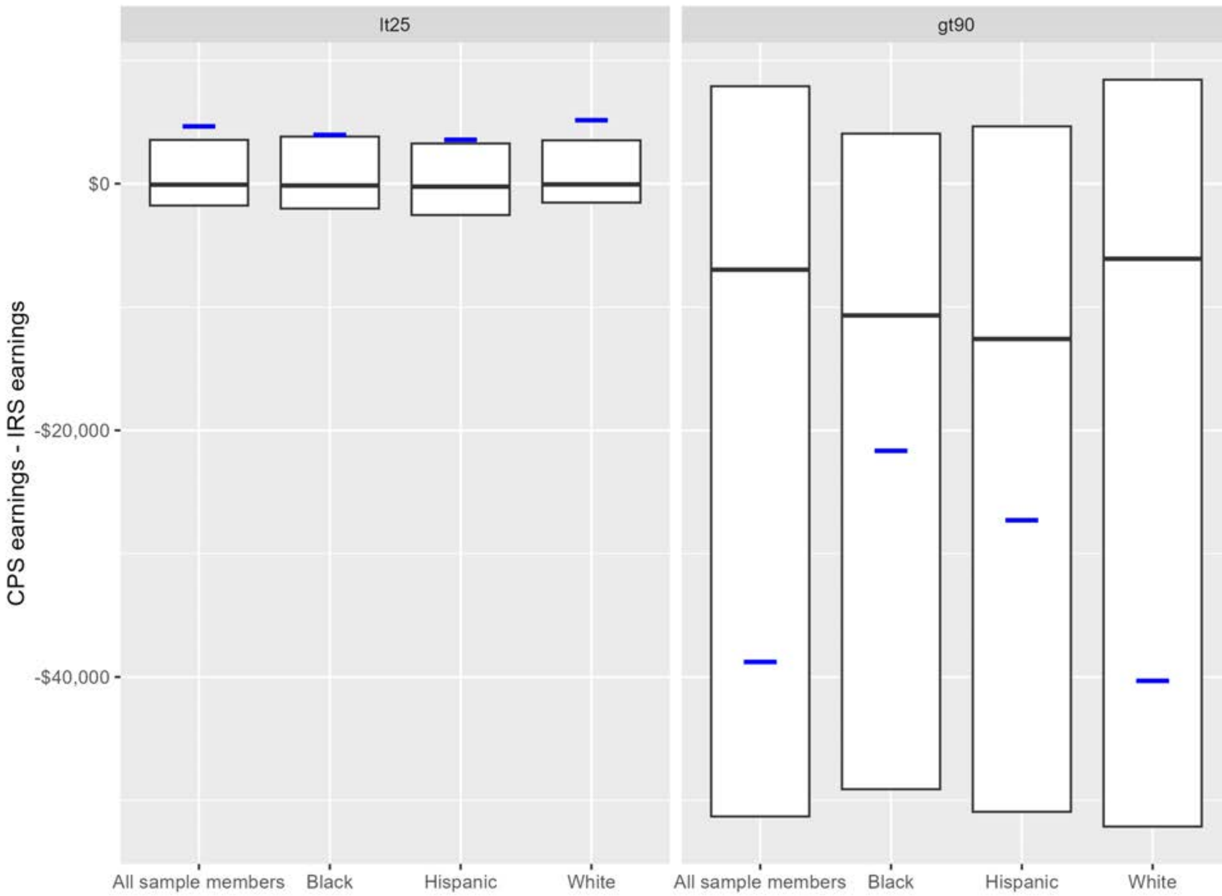


Figure B.7: Respondent-level earnings differences by race and ethnicity

Source: IDDA and Current Population Survey.
Note: Boxplots show the 25th, 50th, and 75th percentiles of earnings differences between individual wage earnings reported in the CPS and IDDA W-2 data. These are reported for Hispanic, non-Hispanic White, and non-Hispanic Black respondents in the bottom 25 percent of individual earnings (left) or the top 10 percent (right), defined using W-2 wage compensation in the linked sample. Release authorization CBDRB-FY23-0373.

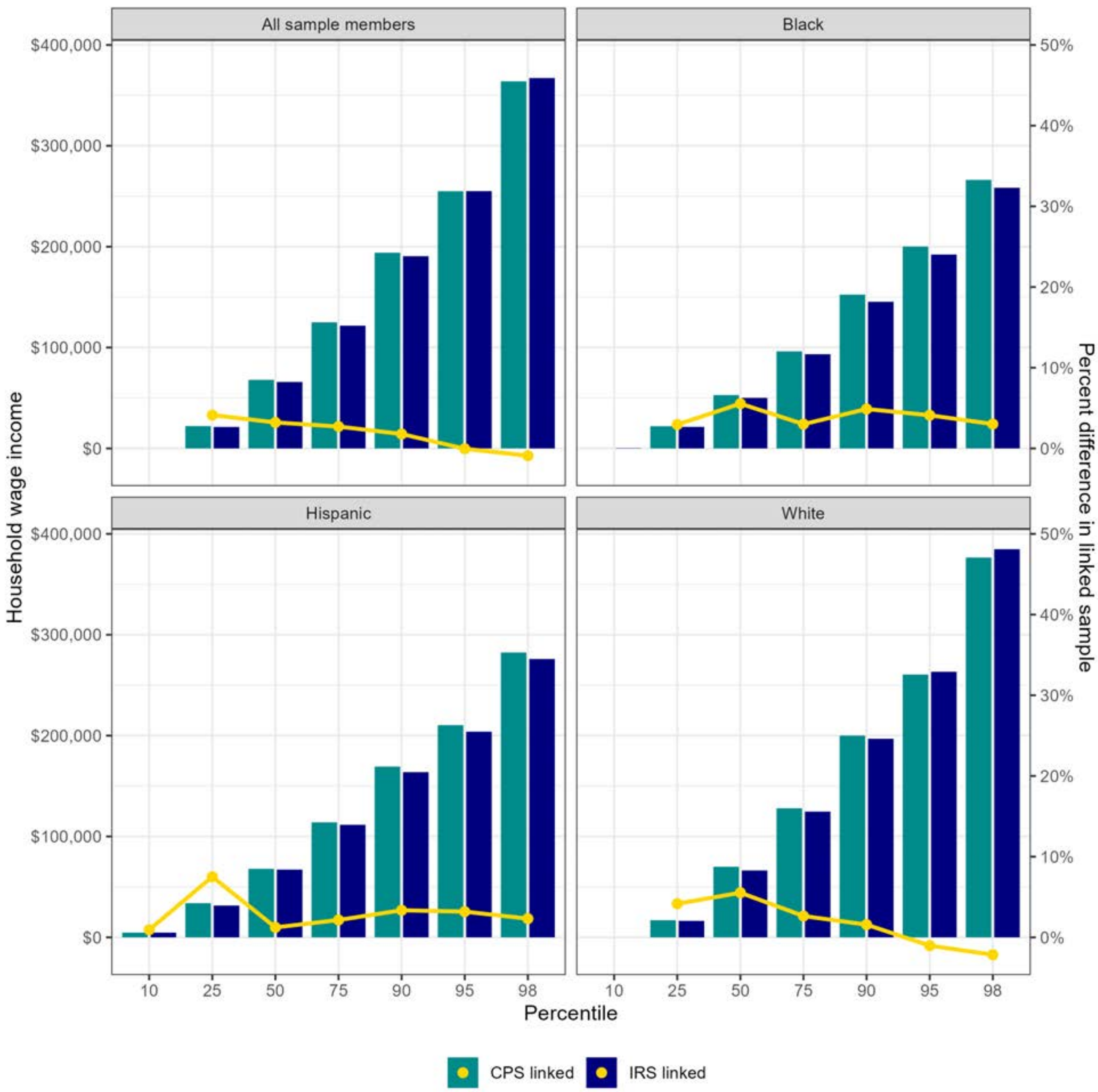


Figure B.8: Distribution of household wage and salary income in matched CPS-IDDA sample, 2019, by race and ethnicity

Source: IDDA and Current Population Survey.
Note: Figure charts selected percentiles of the distribution of household wage and salary income by race and ethnicity in 2019. The linked sample includes CPS ASEC respondents aged 16 or over who can be matched to the IDDA 1040 sample via the PIK, which restricts it to individuals listed as a primary or secondary filer on a Form 1040 filed for tax year 2019. Release authorization CBDRB-FY23-0373.

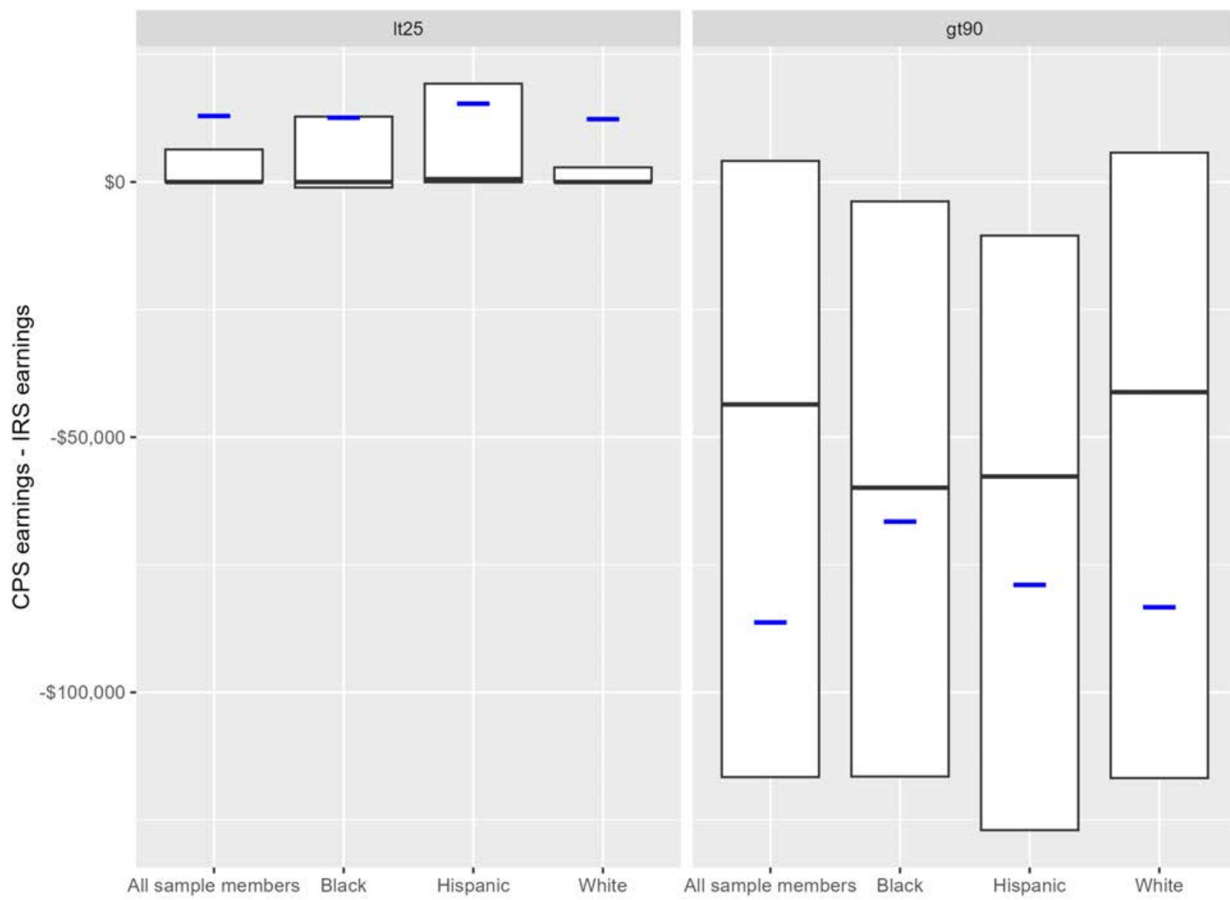


Figure B.9: Household earnings differences by race and ethnicity

Source: IDDA and Current Population Survey.
Note: Boxplots show the 25th, 50th, and 75th percentiles of earnings differences between household wage and salary income reported in the CPS and IDDA 1040 data. These are reported for Hispanic, non-Hispanic White, and non-Hispanic Black respondents in the bottom 25 percent of household wage and salary income (left) or the top 10 percent (right), defined using the 1040 household WSI measure in the linked sample. Release authorization CBDRB-FY23-0373.

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