

# The Feasibility of a Quarterly Distribution of Personal Income

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<b>Abstract</b>	<p>The U.S. Bureau of Economic Analysis (BEA) conducted a feasibility study to evaluate whether it is possible to produce a quarterly distribution of personal income and construct inequality metrics that are valid, informative, and transparent. The primary obstacles to producing such estimates are the lack of available quarterly microdata and inability to follow households over time (panel data). Therefore, we cannot account for household behavioral responses to shocks, such as applying for transfers after a wage loss, or participating in the gig economy, and we miss interdependency of these income sources. In this paper, BEA presents estimates of an interpolated quarterly distribution for 2007–2018. The estimates are driven by changes in aggregate income composition, such that the average of the quarterly estimates for each year is equal to the annual estimate. Many sources of data were considered to improve the quarterly estimates. An in-sample forecast exercise using a simplified methodology shows reasonable results during stable growth years but significantly underestimates inequality during periods of economic volatility (Great Recession and recovery). Forecast results can incorrectly show rising (falling) inequality during quarters when it is falling (rising).</p>
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## 1. Introduction

This report is a feasibility study of quarterly estimates of the distribution of personal income (PI) and disposable personal income (DPI). Though most research on the distribution of income has focused on annual data (BEA, 2020; Auten and Splinter, 2019; Piketty et al. 2018; Congressional Budget Office, 2018), there is some interest in higher frequency quarterly estimates. Table 1 below summarizes some frequently cited inequality estimates, their publication frequency and the years available. Thus far, BEA annual estimates have been as current as those of other authors. The only quarterly estimates available are those extrapolated by the Federal Reserve.

**Table 1. Available Inequality Estimates**

Estimates	Measure	Frequency	Availability
BEA	Personal income and disposable personal income	Annual	2007–2018, soon 2000–2019
Auten and Splinter (2019)	National income (pre-tax and post-tax)	Annual	1960–2015
Piketty, Saez, and Zucman DINA tables	National income (pre-tax and post-tax)	Annual	1913–2019
CBO	Household income pre-and-post-tax	Annual	1979–2018
Census Bureau	Household money income	Annual	1967–2019
World Inequality Database	National income and wealth quantiles	Annual	1913–2019
Federal Reserve Distributional Financial Accounts	Household wealth quantiles	Quarterly	1989Q3–2021Q1 (2019SCF is latest available microdata, so results extrapolated post 2018)

There are several general criteria for distributional national accounts. First, distributional statistics must be valid. Accordingly, we seek to construct metrics that are objectively measurable using the smallest possible set of assumptions to reduce measurement error. A high degree of measurement error is counterproductive in that it may lead to erroneous conclusions about the economy and a potentially inappropriate policy response. The validity of the estimates relies heavily on high quality microdata. Examples of such microdata are survey and administrative datasets produced and carefully compiled by the Census Bureau, the Internal Revenue Service (IRS), the Bureau of Labor Statistics (BLS), and other federal agencies. Although these datasets have shortcomings, such as representativeness at the top (or bottom), limited income variables, and inconsistencies, they are the best available microdata sources for annual income.

Next, distributional statistics should be informative. Given the wide suite of inequality measures currently available, produced by government statisticians, think tanks, and academics, measures produced by BEA should provide additional valuable information linking macro growth (aggregate

income consistent with the U.S. national income and product accounts (NIPAs)) with micro households. Personal income is the measure that is the major component of aggregate income (approximately 87 percent of gross domestic income).

In order for the statistics to be informative, they must have a high signal to noise ratio. That is, they should be attuned to business cycle fluctuations as they pertain to real changes in the income distribution, without introducing measurement error that obscures the trends. We should not expect to see highly volatile distributional metrics during times of stability and growth; conversely, we should expect to see significant shifts in the income distribution with the implementation of new government transfer programs, or with significant job losses, as these reflect business cycle changes in the macro-NIPA series.

Finally, distributional statistics should be transparent. It is important for data users and policymakers to understand how the estimates are constructed and what assumptions are made. We have strived to be as transparent as possible to enable users to better understand the estimates and to be able to compare our results and methods to those of previous studies.

This report proceeds as follows. Section 2 presents a conceptual framework for estimating quarterly distributions of income, beginning with defining BEA's income measures with which we are striving to produce distributional measures. Section 3 presents our initial, prototype estimates of the quarterly distribution of PI and DPI. Section 4 presents a forecasting exercise for the Great Recession. Section 5 provides an overall summary and conclusions.

## **2. Conceptual Framework, Data, and General Issues**

We begin this section by defining personal and disposable income in the NIPAs. With definitions in hand, we next present results from the annual estimates to provide a sense of how quarterly distributions may vary, followed by a discussion on interpreting quarterly results not based on a panel of households. We discuss how we might expect the distribution of PI and DPI to vary over quarters, based on evidence from BEA's estimates of the annual distribution of income and other considerations.

### **2.1 Defining PI and DPI**

In many ways, PI and DPI are not simple measures of cash income received in a given period. PI includes wages and salaries, supplements (employer contributions for employee pension and insurance funds), the income of farm and nonfarm sole proprietors and partnerships, rental income of persons (which consists mostly of imputed owners' equivalent rent, interest income (which includes monetary and substantial imputed interest), dividend income paid to shareholders (but not capital gains from rising stock prices), many types of government social benefits (including health insurance such as Medicaid and Medicare and refundable tax credits), and other transfers, less contributions for government social insurance. DPI equals PI less personal current taxes.

Each of roughly 65 disaggregated components of PI and DPI is subject to seasonal adjustment to remove the average effect of variations that normally occur at about the same time and in about the same magnitude each year—for example, the effect of work schedules, weather, or holidays. If households regularly receive lower pay in certain months, then seasonal adjustment procedures will smooth income over the year such that estimates of the quarterly distribution of top-line PI will not capture these

routinely lower income levels in a specific quarter. The quarterly PI and DPI measures, will, on the other hand, capture unusual changes in income, such as onetime bonuses or income losses, or income changes that accompany periods of recession or recovery.

BEA's estimates of PI and DPI reflect a mix of cash-basis treatment (when pay is received) and an accrual-basis treatment (when the income is legally earned). The international guidelines for national accounts, as explained in the 2008 *System of National Accounts*, recommend an accruals treatment. In practice, the timing of receipt of most components of PI is very similar under a cash- or accrual-basis treatment: most income from wages, social benefits, and other types of income is accrued and paid in the same quarter. For example, large stimulus measures such as the tax credits approved in the second quarter of 2008 as part of the Economic Stimulus Act of 2008, and the economic impact payments approved in the second quarter of 2020, appear mainly in the quarter in which they were enacted. The accrual and cash treatment of some components of PI and DPI, however, differ markedly. Employer contributions to defined benefit (DB) plans, for example, are estimated not as cash contributions but as the accrued change in the employers' liability for entitlements, whether or not the plan is fully funded; DB plan benefits are not counted. Personal current tax payments, refunds, and tax settlements are recorded over the period in which they are earned (typically smoothed over a year), not when actually paid.

Some components of PI are not cash payments that are readily available for spending. PI includes an imputation for owners' equivalent rent, as well as imputed interest and dividends, which homeowners do not actually receive as cash. It includes Medicaid and Medicare, government social benefits that are payments for services and not available for discretionary spending. Because of the inclusion of these noncash and imputed income components, PI is not a simple measure of any abrupt swings in quarterly discretionary income that households may experience tied to sudden economic and policy changes.

## 2.2 Annual Estimates: Review of Methodology and Results

A review of BEA's estimates of the annual distribution of PI and DPI (published December 2020) helps inform our sense of how quarterly distributions may vary. In order to calculate the distribution of PI, we first identify a NIPA total to be distributed (the 65 disaggregated components described above). Because of measurement error and various timing and coverage issues, the sums of each type of household income in microdata data tend to be less than the corresponding BEA aggregates. However, we must allocate the NIPA total to each household. Therefore, we identify variables from the Current Population Survey, Annual Social and Economic Supplement (CPS ASEC) and from external data sources that can be used to allocate this total such that when summed (with household weights), the micro data total will equal the NIPA estimate. Because the ASEC data provide individual-level detailed disaggregated data on many income types, which sum to household, they are critical for the annual estimates, and thus frequently used by inequality researchers.

In order to construct a numerical example of this process, we can suppose there is only one source of income and four sample households, representing a population of 40 people, and our goal is to distribute a NIPA total of \$10,000. However, for this example, the CPS total is assumed to be  $\$100 \times 20 + \$0 \times 10 + \$500 \times 5 + \$400 \times 5 = \$6,500$ . For each household, the share of the CPS total is calculated. Then, this share is multiplied by the NIPA total, as in the example below.

### Example 1. Scaling CPS Values to Annual NIPA Values

Household	Original CPS value	Population weight	Share of total = original CPS value/CPS total	Imputed value = share * NIPA total
1	100	20	$100/6,500 = 0.0154$	$0.0154*10,000 = 154$
2	0	10	$0/6,500 = 0$	$0*10,000 = 0$
3	500	5	$500/6,500 = 0.0769$	$0.0769*10,000 = 769$
4	400	5	$400/6,500 = 0.0615$	$0.0615*10,000 = 615$

When imputed values are multiplied by population weight, they sum to the NIPA total, the same way as the original CPS values sum to the CPS total, when multiplied by the weight:

$\$154*20+\$0*10+\$769*5+\$615*5 = \$10,000$ . For income items that use additional data sources, we first adjust the original CPS value, then proceed the same way.

After all components have been scaled to NIPA totals and added together to compute household and (subsequently) personal income, equivalized personal income is calculated by dividing personal income by the square root of the number of household members. This is done in order to compare households of different size. For example, if household income is \$10,000 and there are four members of the household, equivalized household income is \$5,000 (half of \$10,000). Equivalized rankings of income are used for all income inequality metrics. A more detailed description of the annual methodology (Gindelsky 2020) can be found [here](#).

From 2007 to 2018, the annual share of PI (and DPI) received by all deciles, except for the top 10 percent, varied by less than a percentage point, even over the course of the financial crisis (table 2). The shares of PI received by the bottom decile varied from 1.8 to 2.0 percent, while the share received by the next decile varied from 3.3 to 3.6 percent. At the top of the distribution the share ranged from 34.8 to 38.3 percent for the top decile and from 11.7 to 14.8 percent for the top 1 percent. The results for DPI are similar. In many instances, last year's share of income for a percentile group is a reasonable predictor of the next year's share of income. While the increase in inequality over the last several decades is widely acknowledged among economists, BEA's results imply that this trend has occurred gradually.

The annual estimates also show that different deciles rely mainly on different types of income (table 3). For the lowest deciles, wages and government social benefits are the most important sources of income. For the highest deciles, wages, asset income (interest and dividends) and business income (partnerships and sole proprietorships) are the most important sources of income. As a result, the effect of changes in specific types of income will vary across low- and high-income households; changes in government benefits will have larger effects on the bottom and middle deciles, while changes in asset income will have larger effects on top deciles.

### 2.3 Interpreting the Results without a Panel of Households

Ideally, we would like to observe quarterly changes in the distribution of income for a panel of households over a year.<sup>2</sup> However, there is no dataset that contains quarterly observations of households so as to construct an annual panel (four observations of each household). If we could observe a panel, we might see that household A moves up in the distribution and household B moves down. These movements may change the estimated distribution, or may cancel each other, leaving no change in the estimates of the income distribution. Similarly, if we could see a panel over several quarters, we might find that household B experiences cumulative losses, while household A experiences cumulative gains, or we might see that A and B experience offsetting gains and losses over several quarters, with little change in their cumulative income. But because of the limitations of our existing data sources, we are left with only a series of one-time quarterly “snapshots” of data, or only quarterly changes in aggregate series. Accordingly, we will not be able to understand clearly how changes in households’ quarterly income “add up” to an annual distribution of income.

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<sup>2</sup> The inability to follow households is also a challenge when comparing annual estimates over time. Given that the Census Bureau surveys different households every year, the households in the top 1 percent in 2017 are not those in the top 1 percent in 2018. We hope that the weighting procedures designed to ensure representativeness of the sample help mitigate this problem, though they cannot completely eliminate it. Unlike with administrative data, we cannot, therefore, draw any conclusions about mobility.

Table 2. Annual Distribution of Personal Income and Disposable Personal Income, 2007–2018

	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
<b>Personal income</b>												
<b>Total (\$B)</b>	\$12,008	\$12,442	\$12,059	\$12,552	\$13,327	\$14,010	\$14,181	\$14,992	\$15,724	\$16,161	\$16,949	\$17,852
<b>Eq. Gini</b>	0.443	0.440	0.432	0.429	0.442	0.455	0.447	0.452	0.446	0.446	0.451	0.453
<b>0–10%</b>	2.0%	1.9%	1.9%	2.0%	2.0%	1.9%	1.9%	1.8%	1.9%	1.9%	1.9%	1.9%
<b>10–20%</b>	3.4%	3.5%	3.6%	3.6%	3.5%	3.5%	3.4%	3.3%	3.3%	3.3%	3.3%	3.3%
<b>20–30%</b>	4.4%	4.4%	4.5%	4.5%	4.4%	4.3%	4.3%	4.2%	4.1%	4.2%	4.1%	4.1%
<b>30–40%</b>	5.3%	5.4%	5.5%	5.4%	5.3%	5.2%	5.1%	5.1%	5.0%	5.0%	5.0%	5.0%
<b>40–50%</b>	6.4%	6.4%	6.4%	6.5%	6.4%	6.3%	6.3%	6.2%	6.1%	6.1%	5.9%	6.0%
<b>50–60%</b>	7.5%	7.7%	7.6%	7.8%	7.6%	7.5%	7.5%	7.4%	7.2%	7.3%	7.3%	7.2%
<b>60–70%</b>	9.0%	9.0%	9.2%	9.3%	9.0%	8.9%	9.1%	9.0%	8.9%	8.8%	8.8%	8.8%
<b>70–80%</b>	11.1%	11.3%	11.4%	11.3%	11.0%	10.8%	11.4%	11.0%	11.1%	10.9%	11.0%	10.8%
<b>80–90%</b>	14.7%	14.6%	15.0%	14.8%	14.5%	14.3%	14.3%	14.6%	14.7%	14.6%	14.9%	14.6%
<b>90–100%</b>	36.2%	35.8%	34.9%	34.8%	36.2%	37.4%	36.7%	37.4%	37.7%	37.9%	37.7%	38.3%
<b>Top 5%</b>	26.1%	25.5%	24.6%	24.8%	26.2%	27.5%	26.6%	27.1%	27.4%	27.5%	27.1%	27.9%
<b>Top 1%</b>	13.2%	12.5%	11.7%	12.3%	13.5%	14.8%	13.9%	14.2%	14.1%	14.1%	14.1%	14.4%
<b>Disposable personal income</b>												
<b>Total (\$B)</b>	\$10,515	\$10,935	\$10,907	\$11,314	\$11,873	\$12,501	\$12,505	\$13,207	\$13,784	\$14,203	\$14,902	\$15,767
<b>Eq. Gini</b>	0.409	0.409	0.402	0.397	0.409	0.423	0.411	0.417	0.409	0.409	0.416	0.416
<b>0–10%</b>	2.1%	2.1%	2.1%	2.2%	2.1%	2.1%	2.1%	2.0%	2.1%	2.1%	2.1%	2.1%
<b>10–20%</b>	3.9%	3.9%	3.9%	4.0%	3.9%	3.8%	3.8%	3.7%	3.7%	3.7%	3.7%	3.7%
<b>20–30%</b>	4.9%	4.8%	4.9%	4.9%	4.8%	4.7%	4.8%	4.6%	4.6%	4.6%	4.5%	4.5%
<b>30–40%</b>	5.8%	5.8%	5.9%	5.9%	5.8%	5.6%	5.7%	5.6%	5.6%	5.5%	5.5%	5.5%
<b>40–50%</b>	6.9%	6.9%	6.9%	6.9%	6.9%	6.8%	6.8%	6.7%	6.6%	6.6%	6.5%	6.6%
<b>50–60%</b>	8.1%	8.0%	8.1%	8.2%	8.0%	8.0%	8.0%	7.9%	7.8%	7.9%	7.8%	7.8%
<b>60–70%</b>	9.4%	9.4%	9.6%	9.6%	9.5%	9.3%	9.6%	9.4%	9.3%	9.4%	9.3%	9.3%
<b>70–80%</b>	11.3%	11.5%	11.6%	11.7%	11.3%	11.1%	11.6%	11.3%	11.4%	11.2%	11.3%	11.2%
<b>80–90%</b>	14.5%	14.4%	14.9%	14.6%	14.3%	14.2%	14.3%	14.4%	14.6%	14.6%	14.7%	14.6%
<b>90–100%</b>	33.2%	33.2%	32.2%	32.0%	33.3%	34.5%	33.4%	34.2%	34.3%	34.5%	34.5%	34.7%
<b>Top 5%</b>	23.5%	23.2%	22.3%	22.4%	23.6%	25.0%	23.6%	24.3%	24.5%	24.4%	24.4%	24.6%
<b>Top 1%</b>	11.4%	11.0%	10.3%	10.7%	11.7%	13.0%	11.8%	12.3%	12.0%	11.8%	12.1%	12.1%

Note. This table summarizes the inequality results published in table 3 of the December 2020 release. The first line of each panel provides the total (in billions of dollars) for PI and DPI respectively. The following lines show the distribution of households, ranked on equivalized PI and DPI respectively in each panel by year.

Table 3. Major Components of Personal Income and Disposable Personal Income by Decile, 2018

Line	Income Component	Total (\$B)	0–10%	10%–20%	20%–30%	30%–40%	40%–50%	50%–60%	60%–70%	70%–80%	80%–90%	90%–100%
1	Compensation of employees	\$10,950	1.2%	2.3%	3.1%	4.2%	5.8%	7.8%	10.4%	13.7%	18.4%	33.0%
2	Proprietors' income with inventory valuation	\$1,586	–0.1%	0.2%	0.4%	0.7%	1.0%	1.7%	3.2%	4.5%	9.3%	79.0%
3	Rental income of households with capital consumption adjustment	\$747	1.8%	3.5%	4.7%	5.6%	6.3%	7.3%	8.7%	10.3%	13.4%	38.5%
4	Household income receipts on assets	\$2,886	0.6%	0.8%	1.2%	1.6%	2.3%	3.5%	5.3%	7.6%	12.7%	64.4%
5	Household interest income	\$1,617	0.9%	1.2%	1.7%	2.3%	3.2%	4.6%	6.7%	9.3%	15.0%	55.2%
6	Household dividend income	\$1,268	0.1%	0.3%	0.5%	0.8%	1.2%	2.1%	3.6%	5.4%	9.8%	76.1%
7	Household current transfer receipts	\$3,031	7.2%	10.1%	11.7%	12.8%	12.8%	11.4%	10.2%	8.1%	7.8%	7.9%
8	Gov social benefits	\$2,899	6.6%	10.2%	11.8%	13.1%	13.0%	11.6%	10.2%	8.1%	7.6%	7.8%
9	From business (net)	\$21	8.4%	8.9%	9.2%	9.7%	10.1%	10.5%	10.8%	10.7%	10.7%	11.0%
10	From nonprofit institutions	\$111	23.2%	7.1%	8.5%	5.7%	6.0%	6.7%	10.4%	9.9%	12.4%	10.2%
11	Less: Contrib. for gov social insurance, domestic	\$1,360	1.1%	2.2%	3.1%	4.3%	5.9%	8.1%	10.9%	14.2%	18.9%	31.3%
12	Household income	\$17,839	2.0%	3.3%	4.1%	5.0%	6.0%	7.1%	8.8%	10.8%	14.6%	38.3%
13	<b>Personal income</b>	<b>\$17,852</b>	<b>1.9%</b>	<b>3.3%</b>	<b>4.1%</b>	<b>5.0%</b>	<b>6.0%</b>	<b>7.2%</b>	<b>8.8%</b>	<b>10.8%</b>	<b>14.6%</b>	<b>38.3%</b>
14	Less: Taxes	\$2,085	0.2%	0.4%	0.7%	1.1%	1.9%	3.1%	5.1%	8.3%	14.3%	64.9%
15	<b>Disposable personal income</b>	<b>\$15,767</b>	<b>2.2%</b>	<b>3.7%</b>	<b>4.6%</b>	<b>5.5%</b>	<b>6.6%</b>	<b>7.7%</b>	<b>9.3%</b>	<b>11.1%</b>	<b>14.6%</b>	<b>34.7%</b>

Note. This table represents the breakdown of household income by component as in NIPA table 2.9 (lines 22–33). Personal income (line 13) = Household income (line 12) – Household current transfer receipts from nonprofits + Nonprofit institution income – Nonprofit institution transfer receipts from households. Disposable personal income (line 15) = Personal income – Taxes. Households been ranked by equalized personal income and correspondingly assigned to deciles in the distribution (total = 100 percent).

## 2.4 How Do We Expect the Quarterly Distribution of Income To Vary?

In advance of evaluating any estimates of the quarterly distribution of income, we consider what we expect the “true” quarterly distribution of income to look like, accepting that these prior expectations are somewhat speculative. For there to be quarterly changes in the income distribution, there would have to be changes in the relative positions of households across quarters.

The position in the distribution of household  $hh$  at time  $t$  can be written as

$$HH_{p,t}^h = f[I_t^h, (I_t^h - I_t^{med})]$$

where  $I$  is total income, consisting of capital, labor, and transfer income and  $I^{med}$ , is the median income. If  $I$  for a household changes significantly, then its difference from the median will change, regardless of whether the median itself has changed, and therefore its relative position in the distribution can change. For simplicity, we ignore changes in the number of family members, which can induce relative position changes in equivalized income.

To see this numerically, we can again consider the households from Example 1. Suppose NIPA totals are as follows for each quarter: Q1=\$12,000; Q2=\$10,000; Q3=\$11,000; Q4=\$14,000. However, as we saw in Example 1, shares of each quarter’s total are driven by original CPS values, which are unchanging over the year.

**Example 2. Scaling CPS Values to Quarterly NIPA Values**

	Q1	Q2	Q3	Q4
Person	Imputed value = share * NIPA total			
1	0.0154*12,000 = 184.8	0.0154*10,000 = 154	0.0154*11,000 = 169.4	0.0154*14,000 = 215.6
2	0*12,000 = 0	0*10,000 = 0	0* 11,000 = 0	0*14,000 = 0
3	0.0769*12,000 = 922.8	0.0769*10,000 = 769	0.0769*11,000 = 845.9	0.0769*14,000 = 1076.6
4	0.0615*12,000 = 738	0.0615*10,000 = 615	0.0615*11,000 = 676.5	0.0615*14,000 = 861

Though imputed totals change for each household quarterly, the Gini is calculated to be 0.529 in every quarter because inequality is a relative concept. The relative contribution of each individual is fixed, even though the income level changes. This would be the case if we only have one source of income. However, there is also interdependency in income sources.

Because short-run changes in transfers are determined largely by (infrequent) policy shifts, an ordinary change in position derives primarily from changes in labor and capital income. The stability of the annual changes in capital and labor shares of income implies that either the quarterly changes in the distribution of personal income are similar to the annual changes, or that any volatility averages out

over the year.<sup>3</sup> We might reasonably expect that the quarterly distributions of PI and DPI change little over quarters when the economy is stable and policy changes are minimal (especially as these measures are seasonally adjusted). Over these quarters, the distribution of households with high- and low-wage jobs, with business income, with substantial interest-bearing assets and equities, and with major types of government benefits may be fairly stable. The stability of the annual results also suggests that the quarterly distribution of income may vary little over many consecutive quarters.

Conversely, the quarterly distribution of income might change abruptly in periods of recession or recovery or in periods with major changes in government social benefits or taxes. As the annual results show, changes in government social benefits, wages, asset income, and business income will have different effects on lower- and higher-income households, so rapid changes in these income sources may lead to more pronounced changes in the distribution of income. However, these changes will likely average out over the year. An important test of any method for estimating the quarterly distribution of income will be whether it is informative during these quarters of rapid change.

## 2.5 Additional Data Sources

A major challenge for the quarterly estimates is that the available data sources are currently far less complete than the data available for the annual estimates. Furthermore, like annual data, they are available with a lag. We have investigated whether other data sources can be used to inform the quarterly analysis and they are summarized below, with a detailed assessment of each available in the Appendix.

These data sources investigated can be grouped into several broad categories:

- Survey data on total family income, mainly from the monthly CPS and the Consumer Expenditure Survey (CE), and research by Han et al. (2020)
- Earnings and employment data from the monthly CPS, the Quarterly Census of Employment and Wages (QCEW), the Current Employment Statistics (CES) program, and the quarterly Longitudinal Employer-Household Dynamics (LEHD) program
- Merged earnings and UI data based on tax returns, used by Larrimore et al. (2021)
- The triennial Survey of Consumer Finances (SCF) and recent research (unpublished) by the Federal Reserve Board to use the SCF to estimate quarterly distributions of income
- Private data and research from the Opportunity Insights (2020) program
- Other studies that use private data or a combination of public and private data—Cox et al. (2020), Bartik (2020), and others
- Other studies and data sources

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<sup>3</sup> The standard deviation of the capital/labor share ratio (roughly a third) is 0.018 over the period, with little variation. For the top decile this ratio is about half. Though it falls slightly during the Great Recession, it then rebounds to its original level by the end of the period.

While these data sources provide numerous insights into movements in individual income sources, such as wages or unemployment, none directly provide a joint distribution of income at the household level. Such a distribution is necessary in order to establish the relationship between trends in interdependent income sources on a household level. If a given household receives income from wages and transfers, we are unable to say whether this household has lost wages, but instead received transfers, or to what extent, during an economic downturn. For example, while many taxpayers received the 2008 stimulus checks in 2008Q2, we cannot say which of these households also experienced job loss during this quarter, thus replacing (rather than augmenting) wages. Similarly, we would not be able to say whether these households subsequently chose to participate in the “Gig economy,” increasing earnings via self-employment, in order to offset these losses.

To see this numerically, we can consider two scenarios in Example 3 below. Suppose there are only two households, whose income consists of two aggregated sources: wages and transfers, such that each has a total of \$1,000.

### Example 3. Initial Position

Household	Wage income	Transfer income	Total income
1	\$750	\$250	\$1,000
2	\$250	\$750	\$1,000
<b>Economy total</b>	<b>\$1,000</b>	<b>\$1,000</b>	<b>\$2,000</b>

Initially the two households appear equal. Suppose there is a recession and wage income falls **uniformly** by 20 percent for all households in Q1. Then, wages recover by 10 percent and a policy change provides \$200 of stimulus for every household in Q2. Now we consider the effects in Q1 and Q2.

Q1 – Uniform Shift			
Household	Wage income	Transfer income	Total income
1	\$600	\$250	\$850
2	\$200	\$750	\$950
<b>Economy total</b>	<b>\$800</b>	<b>\$1,000</b>	<b>\$1,800</b>

Q2 – Uniform Shift			
Household	Wage income	Transfer income	Total income
1	\$660	\$450	\$1,110
2	\$220	\$950	\$1,170
<b>Economy total</b>	<b>\$880</b>	<b>\$1,400</b>	<b>\$2,280</b>

First in Q1, the income ratio of household 1 to household 2 is 0.89. Next, in Q2, the income ratio of household 1 to household 2 is 0.95. Thus, inequality has moved in both quarters.

Now suppose aggregate wages still fall by 20 percent, but **non-uniformly** such that household 2 bears the brunt in Q1, while household 1 experienced no wage loss. In Q2, \$200 stimulus benefits have been received by both households, but household 2 has only recovered some wages by picking up part-time work.

Q1 – Non-Uniform Shift			
Household	Wage Income	Transfer Income	Total Income
1	\$750	\$250	\$1,000
2	\$50	\$750	\$800
<b>Economy Total</b>	<b>\$800</b>	<b>\$1,000</b>	<b>\$1,800</b>

Q2 – Non-Uniform Shift			
Household	Wage Income	Transfer Income	Total Income
1	\$750	\$450	\$1,200
2	\$130	\$950	\$1,080
<b>Economy Total</b>	<b>\$880</b>	<b>\$1,400</b>	<b>\$2,280</b>

Unlike in the first scenario, the income ratio of household 1 to household 2 is 1.25 in Q1 and 1.11 in Q2. The relative positions of the two households are reversed. Unfortunately, we do not have panel data and cannot see how individual CPS households are affected by shocks. Therefore, we cannot observe whether an aggregate change is uniform or non-uniform, but past studies using administrative panel data strongly suggest it is non-uniform. Therefore, the only feasible approach for our analysis is to apply the strategy in the first scenario—applying aggregate gains/losses in the economy to all households.

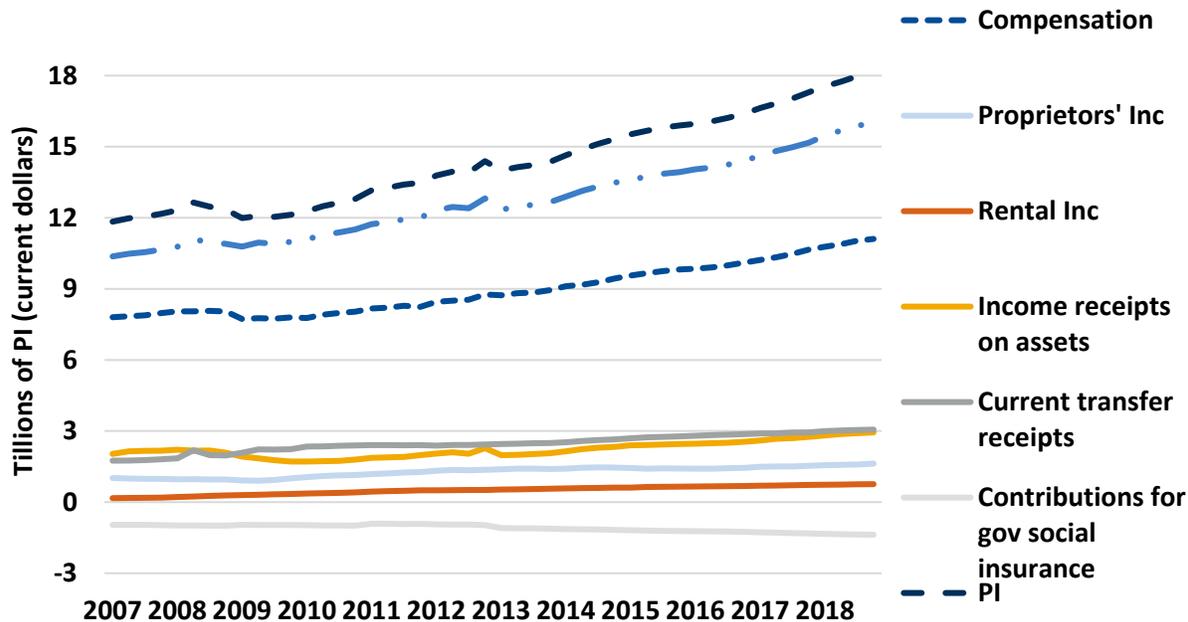
Larrimore et al. (2021) illustrate the limitations of this scenario very effectively in their analysis, which uses individual-level administrative records on wages and salaries and unemployment insurance (UI) benefits, obtained from W-2 and 1099-G forms to find how fiscal relief offset lost earnings in some months of 2020. They found that workers starting in the bottom half of the distribution were more likely to experience large annual earnings declines, but over half of UI beneficiaries in 2020 received at least as much in UI benefits as they had lost in earnings, while others did not. This paper (and others in this large literature) is very effective in conveying the nuance and complexity of these exercises. For example, if we were to use employment patterns showing a large reduction in wages to model 2020 patterns, without knowing that unemployment benefits completely replaced those wages for those at the bottom, we would be falsely inflating income inequality. Conversely, if we applied the increased unemployment benefits to all eligible households without knowing that half did not receive those benefits, we would be falsely deflating income inequality. The large volume of literature in this field supports the notion that these complex relationships make predicting the impact of a specific economic change or transfer extremely difficult.

## 2.6 Quarterly Composition of Total PI and DPI

A review of trends in total PI, DPI, and their major components also helps inform our sense of how the quarterly income distribution may vary (chart 1). As expected, PI and DPI tend to change more abruptly around recessions. Over the 2007–2009 recession, compensation, and dividend income fell while transfers and tax credits rose. This trend was especially notable in 2008q2. Even in some expansion quarters, PI and DPI can display occasional abrupt, one-time changes. An unusually large increase in PI appears in 2012q4, led by increases in compensation and dividend income. However, these increases were due to income re-timing in anticipation of announced increases in top marginal tax rates on labor and capital income in 2013 (Saez 2017). Accordingly, this impact is also seen in inequality metrics, where top income shares rise in 2012 and subsequently fall. These types of one-time events may lead to

transitory changes in the levels and distribution of income. Over most quarters, the levels of PI and DPI changed gradually.

**Chart 1. Quarterly Composition of PI and DPI by Major Income Category, 2007–2018**



Note. Each line in this chart shows the quarterly level of each component of PI and DPI in trillions.

### 3. Initial Estimates of Quarterly Distributions of PI and DPI

In this section, we present estimates of the quarterly distribution of income based on an interpolation of our method for producing annual results, which relies on an enhanced version of the CPS ASEC.

#### 3.1 A Simplified Method for Estimating Quarterly Distributions of PI and DPI

This approach adapts the method used to calculate the BEA’s annual distribution of PI. We estimate the quarterly distribution of income by allocating the aggregate quarterly (annualized) levels of each of the 65 components of PI or DPI proportionately to the sample of households in the CPS ASEC from the same year, so that the sum of each type of income over households equals the quarterly total. Then we estimate quarterly PI or DPI for each household and the distribution of income, after equivalizing households. Under this method, some of the households might move to a different percentile of total income (or a different decile) than in the annual distribution.<sup>4</sup>

At present, there is no micro source of quarterly income distribution data that can be used. Thus, our method assumes that the annual distribution of each type of income for a given year remains constant over the quarters and that changes in quarterly distributions of income will only reflect compositional changes in income.<sup>5</sup> This assumption is consistent with the expectation—based both on the compositional stability of PI and on the annual results—that the distribution of income is fairly constant and changes only gradually over consecutive quarters, barring a major economic event. These quarterly estimates will reflect changes in total levels of specific income components that tend to go to relatively high-income households (like dividends) or low-income households (some social benefits).

#### 3.2 Statistics to Measure the Quarterly Distribution of Income

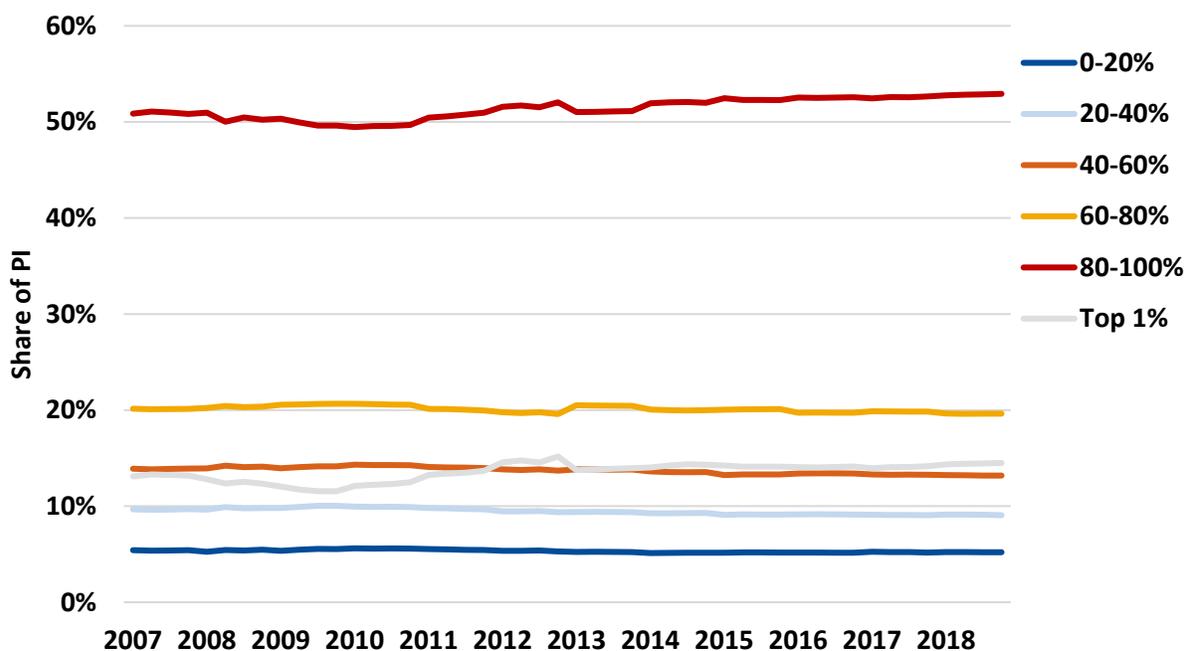
We show interpolated results for quarters from 2007–2018, based on annual samples for each published year (e.g., 2018 quarters are based on the 2018 annual sample). We show the interpolated quarterly trend by quintile (and top 1 percent) for PI and DPI in charts 2 and 3. These charts convey the stability of inequality overall throughout the period. The trends for PI are almost identical to those of DPI. The most volatile series are the top shares (top quintile, driven by volatility of the top 1 percent). In order to directly see the additional volatility from the quarterly series as compared to the annual series, we plot the Gini of equivalized PI for 2007–2018 in chart 4. Chart 4 shows that the quarterly series deviates little from the annual series overall. In fact, the average of the quarterly Ginis is not statistically different than the annual Gini for every year, regardless of volatility. Significant deviations of note are 2012Q4 (due to the timing of income reporting addressed above) and during the Great Recession, as we discuss below.

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<sup>4</sup> Alternative estimates were derived using publication-level detail of PI. This approach relies on the annual shares of 10 major components of PI or DPI received by each decile of households, based on the annual distribution estimates. The major components are compensation, proprietors’ income, rental income, interest income, dividend income, government social benefits (a single sum of all types of benefits), current transfers from business and from nonprofits, contributions for government social insurance (a subtraction item for PI), and personal current taxes (a subtraction for DPI). For each quarter we allocate the total value of each of the major components across the 10 deciles, based on these shares, and then estimate the total income received by each of the deciles. This calculation does not take into account the distribution of more detailed types of income by decile (such as some types of low-income assistance programs) and does not take into account the possibility that some households may move to different deciles as they receive more of less of various types of income. This simplification had little empirical effect on our main results.

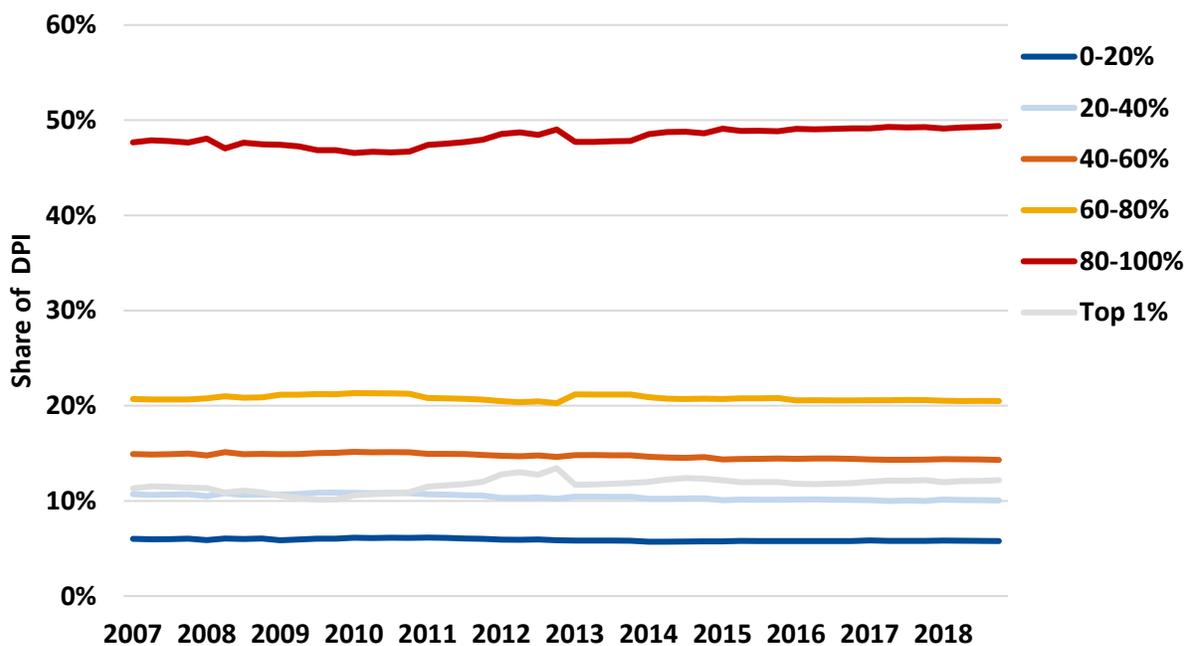
<sup>5</sup> Note that as we receive data with a 2-year lag, these estimates are conducted after the third (latest) vintage and annual revisions have taken place. This reduces additional measurement error that would result from an earlier vintage.

Chart 2. Quarterly PI Distribution, 2007–2018



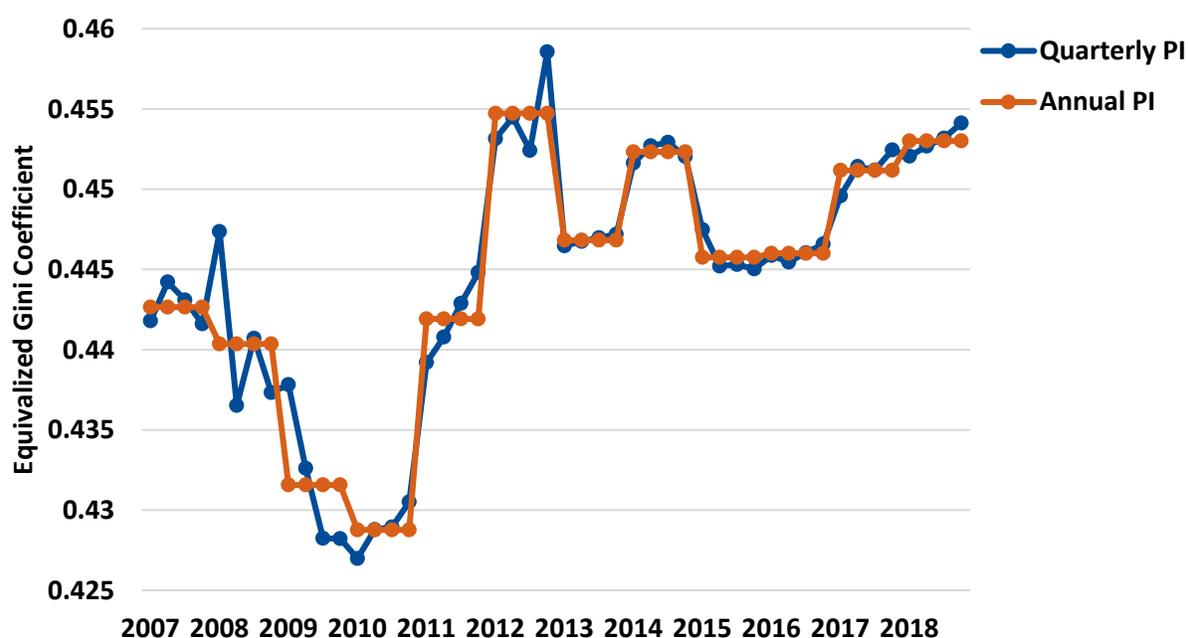
Note. Each line in this chart shows the interpolated quarterly share of household PI. The top 1 percent share is split out from the top quintile (80–100 percent). All households have been ranked on equivalized PI.

Chart 3. Quarterly DPI Distribution, 2007–2018



Note. Each line in this chart shows the interpolated quarterly share of household DPI. The top 1 percent share is split out from the top quintile (80–100 percent). All households have been ranked on equivalized DPI.

Chart 4. Equivalized PI Gini (Quarterly and Annual), 2007–2018



Note. The blue line in this chart shows the interpolated quarterly Gini of equivalized household PI. The red line shows the annual as reported in the December 2020 release. Thus, it is the same (flat) for each within each year.

### 3.3 The Great Recession: 2007–2009

Because one of the key “tests” for our quarterly estimates is to see how they perform during periods of major economic and policy change, we focus on results for the 2007–2009 recession for PI (the results for DPI are very similar). The most striking change in the estimated quarterly income distribution in this period occurred in 2008Q2 when the Gini fell from 0.447 to 0.437 as a result of the fall in interest and dividends and 2008 stimulus. The Gini subsequently slightly rebounded somewhat in the next quarter. Another major fall occurred in the first half of 2009, when compensation remained flat, dividend income fell dramatically while unemployment (and other transfers) increased almost as much as dividends fell. However, as the economy recovered, the Gini rebounded.<sup>6</sup>

To summarize, these estimates of the quarterly distribution of income display some additional variation beyond the annual estimates. The results are in some ways consistent with the trends in aggregate PI, DPI and their major components. Without additional “hard data” on the quarterly distribution of quarterly household income, however, we cannot measure the extent to which these results reflect the limitations of our methodology.

<sup>6</sup> The use of our even simpler “back of the envelope method” also has little impact on our quarterly estimates. In 2008Q2, the shares of household income going to the bottom three deciles are roughly 1–2 percent larger with this simpler method. In other quarters the differences in results from the two methods are trivial. These results demonstrate that quarterly changes in our results are driven mainly by changes in aggregate levels of these major income categories.

### 3.4 Recovery and Expansion: 2010–2018

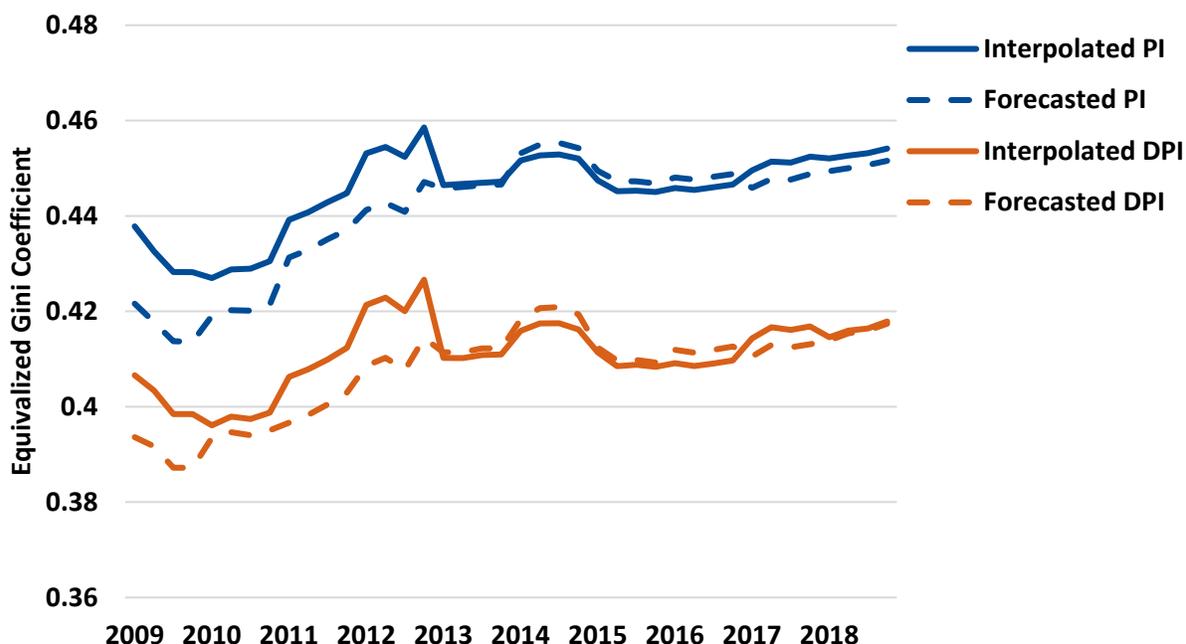
Aggregate PI and DPI display a fairly smooth trend over most of these quarters. Based on our methodology and using the annual household distributions for the same years as the quarters (e.g., 2018 quarters are based on the 2018 annual distribution), our results show that the distributions of PI and DPI vary to some extent over quarters within each year. Within each decile and year, average quarterly household income typically varies by less than 1–2 percent, and by as much as about 3 percent, of average annual household income for that decile and year. The only substantive idiosyncratic shift is 2012 as income reporting responded to announcements of increased tax rates in 2013 affecting top incomes (seen most in Q4), which then revert. The top 1 share is interpolated to be 13.7 percent in 2011Q4 and 2013Q1. Thus, even this period of increased quarterly variation in inequality is representative not of real economic variation, but rather indicative of a temporary behavioral response and should be interpreted accordingly. Otherwise, the small changes in the quarterly income for the top 1 percent of households in each year are attributable to changes in total asset income, business income, and compensation.

## 4. Forecasting Exercise

In order to assess the potential quality of a quarterly forecast, we conduct an in-sample forecasting exercise. Given that we currently receive crucial distributional source data (SOI data from IRS) with a 2-year lag, we conducted an exercise to see whether using a 2-year lagged distribution with current NIPA quarterly data would produce reasonable estimates. In this sense, the exercise is similar to the simplified uniform approach of Example 3 in that the forecast relies on an unchanging distribution with updated income totals, without information on the changes for each household. For example, we forecast the 2009Q1–2009Q4 NIPA data using the annual 2007 interpolated CPS distribution and so on for every quarter until our final estimate of 2018Q4 NIPA data using the 2016 interpolated CPS distribution.

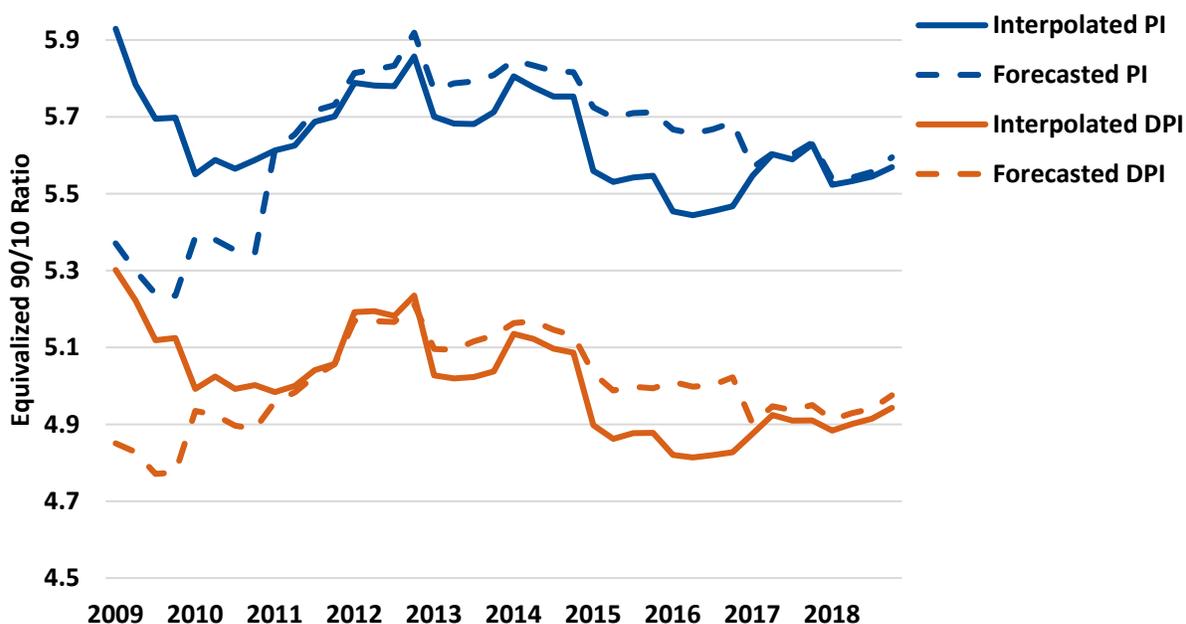
We can see the results of this exercise by taking different slices of the distribution in charts 5–9. Chart 5 shows the interpolated and forecast equivalized Gini for 2007–2018 PI and DPI. The results are fairly straightforward to interpret. The forecast consistently underpredicts inequality for PI and DPI throughout the Great Recession and beginning of its recovery, while predicting fairly well during the stable growth period (2013–2018). The average forecast error for the quarters of 2009 (0.015) is larger than the growth in the Gini over the entire period (0.012) (Note, this is already a slightly larger statistical increase than actual inequality due to the CPS survey methodology change in 2018). Chart 6 presents the same exercise for the 90/10 ratio, commonly used to assess inequality without as much influence from the tails, which can influence general inequality metrics such as the Gini, by including the most extreme income values. Here again, the error is very large for the Great Recession period, where the 90/10 ratio is underestimated by an average of 0.5 for 2009 quarters, though it only falls by 0.36 from 2007–2018.

**Chart 5. Forecasted vs. Interpolated Quarterly Eq. Gini of PI and DPI, 2009–2018**



Note. The solid lines in this chart show the Gini of equalized household PI (blue) and DPI (red) interpolated quarterly. The dashed lines show the same series forecasted. This forecast is constructed for every quarter by using a 2-year lagged annual distribution for each NIPA quarter. As our annual distribution presently spans 2007–2018, the first available interpolated quarterly distribution is 2007Q1. Therefore, the first forecasted quarter can be 2009Q1, which uses NIPA macro totals from 2009Q1 with the annual micro distribution of 2007. In this way, the chart models the possibility of forecasting quarterly inequality series with available data at that time (2-year lagged).

**Chart 6. Forecasted vs. Interpolated Quarterly Eq. 90/10 Ratio of PI and DPI, 2009–2018**

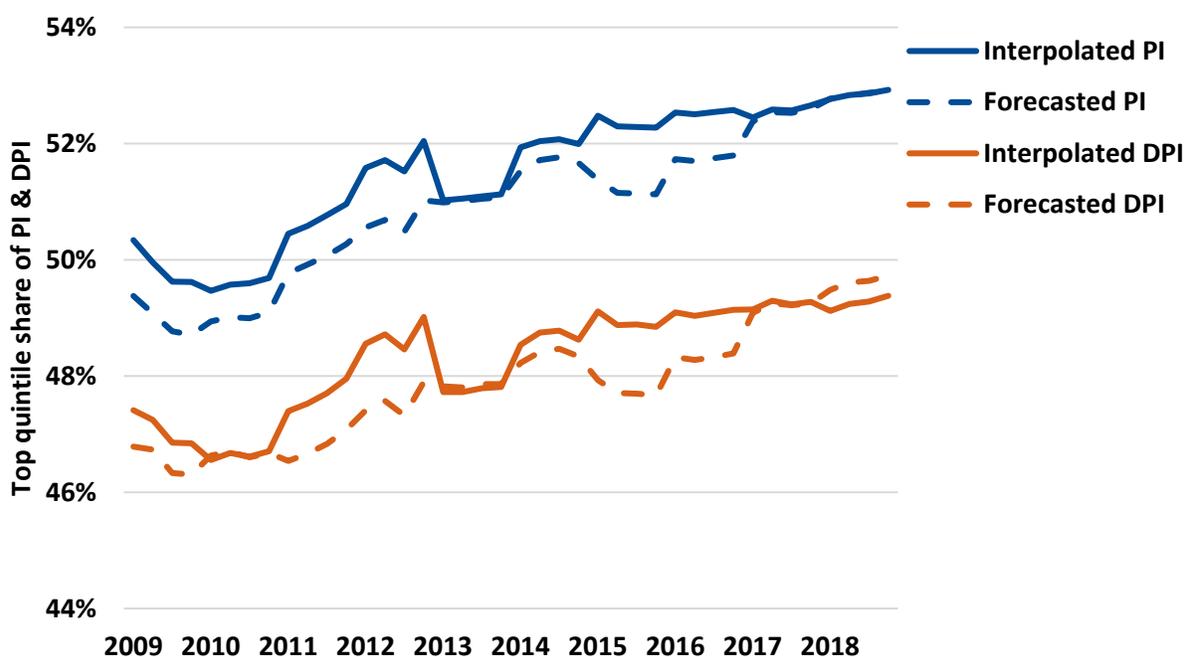


Note. This chart repeats the method of chart 5 using the 90/10 ratio, rather than the Gini. The 90/10 ratio is the equalized household PI (or DPI) at the 90th percentile/the equalized household PI (or DPI) at the 10th percentile.

To narrow down the source of the large errors, we separately looked at top shares (charts 7 and 8) and bottom shares (chart 9). The forecast for the bottom 10 percent overestimates the interpolated values slightly during the Great Recession. However, the trends are a bit more complicated for the top quintile and top 1 percent. Generally, the forecast underestimates the share of the top quintile by a significant amount (about a percentage point). Though it does track closely in 2013, this is due to the timing issue causing inequality to return to 2011 levels, rather than because of the success of the model. For the top 1 percent, the forecast appears fairly accurate for 2009 and then underperforms significantly in the following years, until 2013 and actually overperforms afterwards.

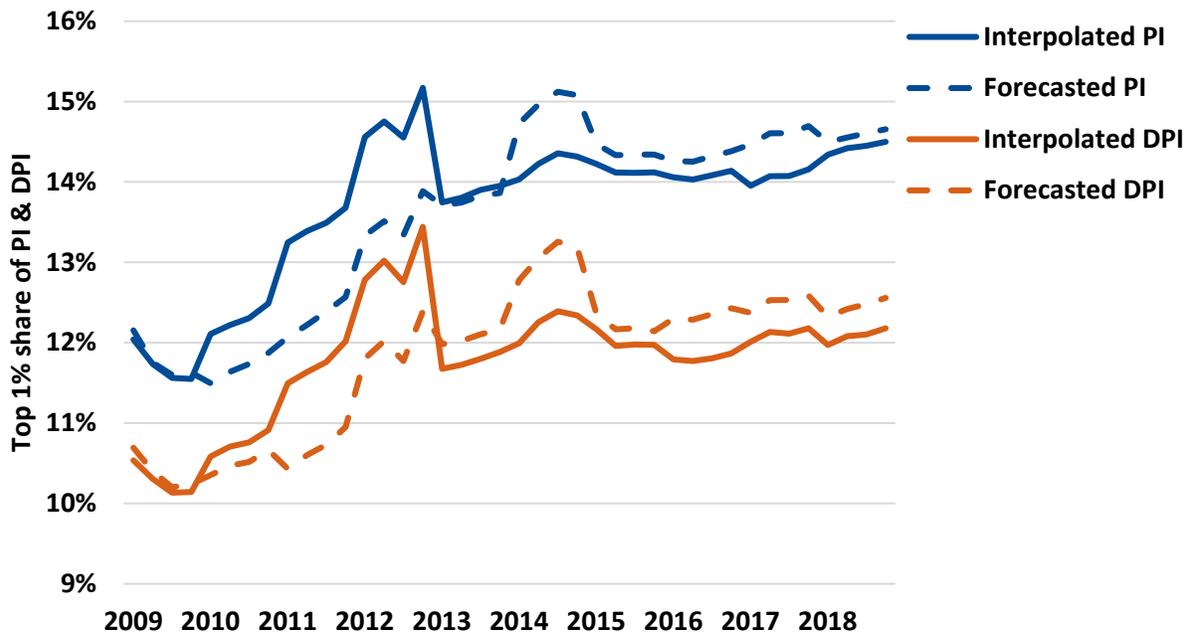
Overall, this exercise shows that attempts to forecast with a 2-year lag lead to large measurement errors. Given that it is precisely during periods of economic turbulence when we see the most quarterly fluctuations, it would be especially important to minimize forecast error at those times.

**Chart 7. Forecasted vs. Interpolated Quarterly Top 20% Share of PI and DPI, 2009–2018**



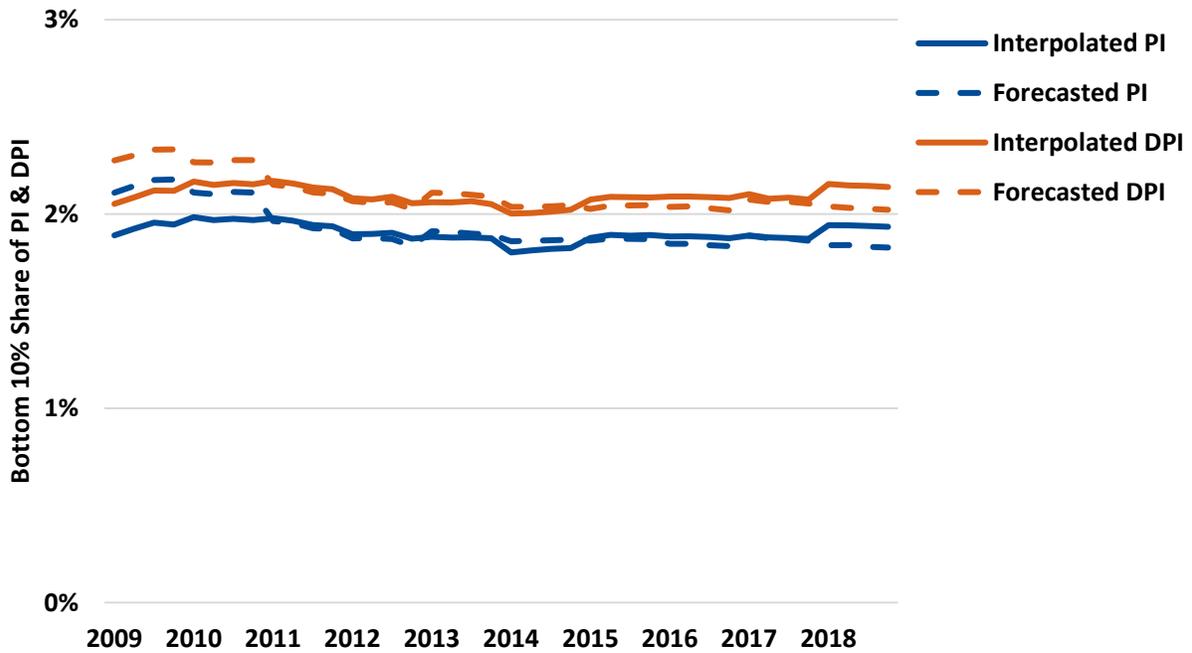
Note. This chart repeats the method of chart 5 using the top 20 percent share of PI and DPI. All households have been ranked on equivalized income.

**Chart 8. Forecasted vs. Interpolated Quarterly Top 1% Share of PI and DPI, 2009–2018**



Note. This chart repeats the method of chart 5 using the top 1 percent share of PI and DPI. All households have been ranked on equivalized income.

**Chart 9. Forecasted vs. Interpolated Quarterly Top 10% Share of PI and DPI, 2009–2018**



Note. This chart repeats the method of chart 5 using the top 10 percent share of PI and DPI. All households have been ranked on equivalized income.

## 5. Summary and Conclusions

In response to interest in measures of the income distribution that are produced more rapidly and more frequently than the existing annual estimates, BEA has conducted a feasibility study for developing estimates of quarterly distributions of personal income (PI) and disposable personal income (DPI). These new statistics should meet BEA's existing quality standards and should provide new, meaningful information. Estimates should be well defined with a transparent methodology, be relatively stable, and yield revisions that do not undermine the reliability of the estimate.

These new statistics would need to be interpreted carefully, as quarterly PI and DPI are not simple measures of discretionary cash income but instead seasonally adjusted, accrual-basis measures that also include measures of imputed income and payments for health care services financed by Medicare and Medicaid. The absence of quarterly panel data—which would allow us to see how households rise and fall in the income distribution over consecutive quarters—further complicates the interpretation of estimates. As we evaluate any estimates, we may, for several reasons, reasonably expect inequality to vary less over quarters with minimal economic and policy change, but perhaps more in periods of major economic and policy changes.

The main obstacle to producing high-quality quarterly estimates of the distribution of income is that the available data are not as informative as the available data for the annual estimates. The primary reason for this is that there are no micro distributions of quarterly income available. Instead, the approach used is to hold an annual micro distribution constant and interpolate quarters using macro variation. Our method is thus similar in nature to, but more nuanced than, that of the Federal Reserve in its Distribution of Financial Accounts, which keeps the micro distribution constant triennially, as aligned with the SCF.<sup>7</sup>

In this report, we show initial estimates of an interpolated quarterly distribution of income based on a simplified method. We assume that the distribution of each of the components of income from BEA's annual estimates from the current or most recent year remains the same in a quarter. This method will capture changes in distribution driven by changes in the composition of income components; changes in government benefits tend to raise the income shares of lower-income households, while changes in business and asset income tend to raise the income shares of higher-income households. This method will not, however, capture quarterly changes in the underlying distribution of each type of income within a year. As a result, it may lead to biased estimates, especially in periods of rapid economic and policy changes. Specifically, this method may understate the loss of income in low-income households in a recession when these households incur a larger share of earnings losses because we allocate these earnings losses proportionately (so that higher-income households incur much of the loss).

Our results show that the interpolated quarterly distribution tracks the annual distribution well overall. The deviations are mainly due to the timing of transfer payments in the Great Recession (e.g., 2008Q2 stimulus) as well as income reporting timing (e.g., 2012). However, these estimates were done using already available annual data for those years. Attempts to forecast the quarterly distribution using 2-year lagged annual data performed adequately (reasonably accurate) during stable economic periods.

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<sup>7</sup> The weaknesses of keeping the micro distribution constant when extrapolating are evident in chart 1 of this [note](#) shows large measurement error in estimating the top 1 percent for 2016–2019, a relatively stable growth period, without the availability of a 2019 SCF.

However, the forecast performed poorly (significantly underestimating inequality) during the Great Recession, when there was significant quarterly variation. In the case of the overall inequality measures (Gini and 90/10), the size of the forecast error in 2009 is greater than the entire magnitude of the change in inequality over a 12-year period.

While transparent, these forecasts have significant errors, which limit their utility to policy makers. In the in-sample exercise, they sometimes incorrectly predict rising inequality when it is in fact, falling, and the reverse. Interpreting these results would then be misleading to those seeking to evaluate a change in inequality resulting from shifting economic conditions or policies. We invite comments in order to help formulate next steps. We are especially interested in specific, concrete suggestions as to how to use existing data sources in creative ways to improve these estimates.

## Appendix: Data Sources Examined

### 1. Survey Data on Family Income and the Consumer Expenditure Data

#### a. Monthly CPS

We first examine the monthly CPS, which collects labor force data for a large representative sample of U.S. households and releases data within a few weeks after the end of a month. The monthly CPS asks for a single estimate of total family income (in categorical ranges) over the past 12 months. This measure includes money from jobs, net income from business, farm or rent, pensions, dividends, interest, social security payments, and any other money income received by family members who are at least 15 years old; it is roughly similar in scope to the annual CPS ASEC measure of household income. The monthly CPS also obtains data on usual weekly earnings for wage and salary workers (excluding self-employed). Weekly earnings are measured before taxes and other deductions, and include overtime pay, commissions, and tips (at the main job, in the case of multiple jobholders). Earnings reported on a basis other than weekly (annual, monthly, hourly) are converted to weekly earnings. The monthly CPS, like the CPS ASEC, also provides data on the demographic characteristics, industry, occupation, and location of respondents. BLS uses these data to publish estimates of the distribution of quarterly earnings (medians, quintiles, and deciles) for full-time workers.<sup>8</sup> However, using only full-time workers would significantly bias the inequality distribution, and critically so during economic downturns.

The family income data in the CPS also have several limitations. The CPS asks only about income from the last 12 months rather than quarterly income. The sample sizes are limited: the CPS collects the data from only about one fourth the total sample each month (first and fifth interview months) and an additional roughly 20 percent does not respond. (Han et al. (2020) used samples of about 9,200 families in April 2019 and about 6,100 in April 2000.) Responses could suffer from recall biases (such as giving more weight to more recent months). The survey question covers only a cash definition of income, reports only ranges of income with topcoded values, and reports only a single estimate of total income rather than separate estimates of income from several sources (like the CPS ASEC). Han et al. (2020) acknowledge these issues and also suspect that the shift in income from earnings, a well-reported source of income, to UI, a poorly reported source, means that they may have understated improvements or overstated declines in income.<sup>9</sup> As shown in Han et al. (2020), some volatility information may be gained when substantial changes occur in the most recent quarter, as happened in early 2020; in other periods, the interpretation of these results may be less clear.<sup>10</sup> Moreover, it is

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<sup>8</sup> To address the tendency for the distribution of responses to appear as spikes at round numbers, rather than as more precise estimates, the BLS procedure for estimating the median of an earnings distribution places each reported or calculated weekly earnings value into a \$50-wide interval that is centered around a multiple of \$50. The median is calculated through the linear interpolation of the interval in which the median lies. For more information on the monthly CPS, see the [BLS](#) and [Census Bureau](#) documentation. The labor force questionnaire can be found [here](#). For more information on weekly earnings, including the BLS data on the distribution of quarterly earnings for full-time workers, see [BLS documentation, news release, and tables](#). In 2020, the Census Bureau added [additional questions](#) about the effects of the pandemic on employment outcomes.

<sup>9</sup> In recent years, about ninety percent of earnings has been reported in the CPS, as opposed to only about sixty percent of unemployment insurance (Meyer et al. (2015)). The CPS family income question also omits the income of persons in the household who are outside the householder's family (unrelated persons and subfamilies, about 5 percent of persons).

<sup>10</sup> Specifically, from one quarter to the next, the estimated 12-month family income estimates change (assuming no recall bias etc.) because we observe the responses from the most recent quarter for the first time, and because we no longer observe the responses from the quarter one year ago. If the distribution changes from one quarter to the next, we need to make an assumption as to whether a change in the distribution happened in most recent quarter, or in the quarter from a year ago, or both. In an extreme event such as the pandemic, we can reasonably assume (as Han et al. (2020) did) that the change occurred

unclear how this information would be applied to adjust the annual CPS ASEC. Much of the same information on downturns is evident from shifts in NIPA totals. The monthly CPS weekly earnings data have additional limitations: the data cover only the reference week and not an entire quarter; the data are not seasonally adjusted; and sample sizes are limited because the data are collected for only about one-fourth of survey respondents.

### **b. Consumer Expenditure Survey (CE)**

The CE is a nationwide household survey conducted by the Census Bureau for BLS and provides information on consumers' expenditures, incomes, and demographic characteristics. Each consumer unit in the sample (CU, similar to families or households in the CPS) is interviewed every 3 months over four calendar quarters. In the first and fourth quarterly interviews, the CE asks CUs about income received over the past 12 months from each of several sources, including not only earnings but also government benefits; interest and dividend income, and rental and self-employment income.<sup>11</sup> BLS publishes 12-month estimates of consumer expenditures and income twice a year (every 6 months), including estimates for quintiles and deciles of the income distribution. In discussions with BLS, they have stated that the CE data cannot be used to infer any quarterly distribution information due to limitations of the survey design.

## **2. Earnings and Employment Data**

### **a. Quarterly Census of Employment and Wages (QCEW)**

The QCEW produces comprehensive data on the number of establishments, employment, and wages for workers covered by State and Federal unemployment insurance (UI) programs. The quarterly wage data are available roughly 5 months after the end of the quarter, by 6-digit North American Industry Classification System (NAICS) category and by state, county and metropolitan statistical area. The QCEW generally reports total wages paid before taxes, including irregular pay such as bonuses. BEA uses seasonally adjusted QCEW data to estimate wages and salaries in PI.<sup>12</sup> While informative, this aggregated data is not appropriate for a micro analysis.

### **b. Current Employment Statistics (CES)**

Monthly data produced from the CES survey of establishments, available within 30 days after the end of the month, include nonfarm employment series for all employees, production and nonsupervisory employees, and female employees, as well as average hourly earnings, average weekly hours, and average weekly overtime hours (in manufacturing industries) for both all employees and production and nonsupervisory employees by six-digit NAICS industry and by location. BEA uses the monthly CES data for estimates of wages for monthly PI and for quarterly wage estimates before the QCEW are available. While informative, this aggregated data is not appropriate for a micro analysis. Based on our own calculations, trends in weekly earnings in the CPS and CES are not always similar. The extent of the

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in the most recent quarter. In smoother periods, estimating changes in the distribution in the most recent quarter could be more difficult.

<sup>11</sup> The CE obtains data on wages and salaries, net room/rental income, self-employment income, public assistance, social Security and railroad retirement income, food stamps, supplemental security income, lump sum payment received, interest and dividends, other income, retirement, survivors, disability income, other regular income, royalty, estate, trust income, income before taxes. There are also binary indicators about whether someone receives government benefits or participates in a pension plan, though monetary values are unavailable.

<sup>12</sup> See the BLS [documentation](#) on the QCEW.

differences in patterns varies by industry. The publicly available QCEW and CES data do not provide the distributions of earnings, only total earnings for available subgroups.

### c. Longitudinal Employer-Household Dynamics ([LEHD](#))

The LEHD program at the Census Bureau produces public-use information combining federal, state and Census Bureau data on employers and employees. States provide QCEW data, and the LEHD program combines these and other administrative data with data from censuses and surveys. From these data, the program creates statistics at detailed levels of geography and industry and for different demographic groups, published on a quarterly schedule with a roughly three-quarter publication lag. The LEHD provides the Quarterly Workforce Indicators (QWI), a set of economic indicators including employment, job creation, earnings, and other measures of employment flows. The Job-to-Job Flows (J2J) program produces statistics on job-to-job transition rates, hires and separations to and from employment, earnings changes due to job change, and characteristics of origin and destination jobs for job-to-job transitions.

The main weakness of all these data is that they lack information on other sources of income received by all household members. They cannot reveal whether declines in earnings were offset by increases in government benefits within households.

### 3. IRS records on earnings and UI benefits ([Larrimore, Mortenson, and Splinter \(2021\)](#))

Larrimore et al. (2021) obtained annual samples of individual-level administrative records on wages and salaries and UI benefits, obtained from W-2 and 1099-G forms drawn from the population of IRS tax records. They supplement these data with IRS records on receipt of economic impact payments (EIPs). This paper documents the magnitude and distribution of U.S. earnings changes during the COVID-19 pandemic and how fiscal relief offset lost earnings. They found that in 2020, workers starting in the bottom half of the distribution were more likely to experience large annual earnings declines and a similar share of male and female workers had large earnings declines. They also found that most workers experiencing large annual earnings declines did not receive UI, over half of UI beneficiaries in 2020 received at least as much in UI benefits as they had lost in earnings. This paper provides important information on how unemployment benefits offset wage losses for the specific months under study and shows the nuance and complexity of undertaking an exercise with so many different sources of income.

### 4. The Survey of Consumer Finances

The Survey of Consumer Finances (SCF) is a triennial cross-sectional survey of U.S. families (the most recent data are from 2019) that collects information on families' balance sheets, pensions, sources of income, and demographic characteristics. For its estimates of the quarterly distribution of wealth accounts, the Federal Reserve Board starts with the SCF to obtain distributional wealth estimates and then uses aggregate quarterly data from the FRB's Financial Accounts of the US, and other data, to interpolate and extrapolate quarterly estimates (see [Batty et al \(2019\)](#)).

In unpublished work, still in progress, researchers at the Federal Reserve Board measured the distribution of income for each quarter since 1988 using household-level data from the SCF. They constructed an adjusted version of PI which is consistent with the income measure captured in the SCF. For the periods in which there is an SCF observation, they observed the amount of income held by each quintile of the distribution (and the top 1 percent)—as they relate to a set of economic indicators and applied the temporal disaggregation method presented in Fernandez (1981) to estimate each group's

income for quarters in which the SCF is not available. Then they estimated the share and the amounts of income held by each income group. The authors state that the new measure falls largely in line with existing measures of the income distribution, and that their results are consistent with previous research that has reported a “middle class squeeze” in which the top of the distribution (the top 1 percent) gains share of income and wealth at the expense of the middle class (the group between the median and 90th percentiles).

The strategy of the Fed involves creating percentiles of wealth (bottom 50, 50-90, 90-99, top 1) using the SCF. They calculate the average wealth for each household in these percentiles and then interpolate and extrapolate these series quarterly using the Fernandez method. In their more recent paper, they create percentiles of income by quintile.

This innovative study has limitations, which the authors acknowledge. They have only 11 observations from the triennial SCF available during this period, with the latest SCF conducted in 2019. The indicators used for the Fernandez method are limited to the aggregate adjusted NIPA income measure, the civilian employment-population ratio, the S&P 500, and the real Federal Funds rate. The study provides interesting estimates but lacks detailed indicators of quarterly movements of total income for percentile groups of households, especially lower income deciles. This strategy relies on an unchanging distribution of income (or wealth) and only allows income shares to be created explicitly for the chosen income percentiles (in this case, quintiles). The strategy of the BEA involves scaling CPS microdata to NIPA totals to create an entire micro distribution of income, as compared to specific percentiles. Thus, BEA is able to construct any income inequality metrics desired, including the Gini coefficient, income deciles, top 5 percent and so on. An exercise comparing the two strategies for wages (since this is measured most consistently) showed very similar results overall for the defined set of percentiles.

Moreover, the weaknesses of keeping the micro distribution constant when extrapolating are evident in chart 1 of this [note](#) shows large measurement error in estimating the top 1 percent for 2016–2019, a relatively stable growth period, without the availability of a 2019 SCF.

## 5. Opportunity Insights

[The OI Economic Tracker](#) is a freely available interactive website that measures economic activity at a high-frequency, granular level, often available in a matter of days. It uses anonymized data from several large businesses—credit card processors, payroll firms, job posting sites, and financial services firms—to construct statistics on consumer spending, employment rates, incomes, business revenues, job postings, and other key indicators. The OI tracker disaggregates the data by county and by industry and, where possible, by initial (pre-crisis) income level and business size. It addresses concerns about privacy by reporting only changes since January 2020 (rather than raw levels), masking small cells, and pooling data from multiple companies to comply with regulations governing the disclosure of information.

[Chetty et al 2020](#) illustrates how the tracker can be used to measure the economic impacts of the COVID-19 crisis on people, businesses, and communities. They show that high-income individuals (defined as those in high-income ZIP codes) reduced spending sharply in mid-March 2020, particularly in areas with high rates of COVID-19 infection and in sectors that require in-person interaction. This reduction in spending greatly reduced the revenues of small businesses in affluent ZIP codes. These businesses laid off many of their employees, leading to widespread job losses especially among low-wage workers in affluent areas. High-wage workers experienced a “V-shaped” recession that lasted a few weeks, whereas low-wage workers experienced much larger job losses that persisted for several

months. They use their data to estimate the effects of policies aimed at mitigating the impacts of COVID-19.

This research provides extensive information about changes in employment, consumer spending, UI claims, and small business revenues for high- and low-income ZIP codes. The use of this data, or extensions of these data, is currently limited to spatial inequality discussions.

## 6. Studies using private data sources

### a. Bartik et al. (2020)

[Bartik et al \(2020\)](#) document the collapse and subsequent partial recovery of the U.S. labor market in Spring 2020 -- using the monthly CPS, the CES, UI claims data and a private data source - daily work records compiled by Homebase, a firm that provides time clocks and scheduling software to mostly small businesses. Their data show that this sudden recession was driven by low-wage services, particularly the retail and leisure and hospitality sectors. A large share of the job loss in small businesses reflected firms that closed entirely. Nevertheless, most laid off workers expected to be recalled, and many businesses reopened and rehired their employees. More disadvantaged workers (less educated, non-white) were more likely to be laid off and less likely to be rehired.

### b. Cox et al. (2020)

[Cox et al \(2020\)](#) use US household-level bank account data to investigate the effects of the pandemic on spending and savings for low- and high-income groups. Households across the income distribution reduced spending from March to early April. After early April, spending grew most rapidly for low-income households. While liquid asset balances grew for both high- and low-income households, lower-income households contribute disproportionately to the total increase in balances, relative to their asset shares before the pandemic, suggesting that government policies played an important role in limiting the effects of labor market disruptions on spending rates. The reasons for increases in saving differed for higher and lower income households. For higher income households, savings rose because spending (especially nonessential spending) fell at the top of the income distribution. For lower income households, increases in unemployment lowered saving but this effect was offset by government programs like the economic impact payments (EIPs) and expanded unemployment insurance (UI), which raised asset balances. [Greig et al. 2021 \(JP Morgan Chase Institute\)](#) provided an update of these findings based on additional months of administrative banking data.

## 7. Administrative records of government benefit programs

We looked for, but could not find, useful monthly or quarterly administrative data on income sources of households that receive government social benefits. We had hoped to use these records to learn about possible changes in the distribution of household income, but these data do not appear to be available. For example, we searched but were not able to find data on the quarterly or monthly income of nationally representative samples of households that received UI benefits. Estimating levels of quarterly UI benefit receipt by household is complex. Benefits depend on earnings histories that the monthly CPS does not provide.

## References

- Auten, G., and D. Splinter. 2019. "Top 1 Percent Income Shares: Comparing Estimates Using Tax Data." *AEA Papers and Proceedings* 109 (1): 307–311.
- Bartik, A.W., M. Bertrand, F. Lin, J. Rothstein, and M. Unrath. 2020. "Measuring the labor market at the onset of the COVID-19 crisis." *Brookings Papers on Economic Activity* (June).
- Batty, M., J. Bricker, J. Briggs, E. Holmquist, S. McIntosh, K. Moore, S. Reber, M. Shatto, T. Sweeney, and A. Henriques. 2019. "Introducing the Distributional Financial Accounts of the United States."
- Chetty, R., N. Hendren, M. R. Jones, and S.R. Porter. 2020. "Race and Economic Opportunity in the United States: An Intergenerational Perspective." *Quarterly Journal of Economics*, 135(2):711–783.
- Congressional Budget Office. 2018. "The Distribution of Household Income and Federal Taxes, 2014." CBO report.
- Cox, N., P. Ganong, P. Noel, J. Vava, A. Wong, D. Farrell, and F. Greig. 2020. "Initial impacts of the pandemic on consumer behavior: Evidence from linked income, spending, and savings data." *Brookings Papers on Economic Activity*.
- Fixler, D., M. Gindelsky, and D. Johnson. 2020. "Measuring Inequality in the National Accounts." *BEA Working Papers*, WP 2020–03.
- Gindelsky, M. 2020. "Technical Document: An Updated Methodology for Distributing Personal Income." [technical-document-a-methodology-for-distributing-personal-income.pdf](https://www.bea.gov/technical-document-a-methodology-for-distributing-personal-income.pdf) (bea.gov)
- Greig, F., E. Deadman, and P. Noel. 2021. "Family cash balances, income, and expenditures trends through 2021: A Distributional Perspective." JPMorgan Chase Institute.
- Han, J., B. Meyer, and J.X. Sullivan. 2020. "Income and Poverty in the COVID-19 Pandemic," *Brookings Papers on Economic Activity*.
- Larimore, J., J. Mortenson, and D. Splinter. 2021. "Earnings Shocks and Stabilization During Covid-19". Board of Governors of the Federal Reserve System. Finance and Economics Discussion Series 2021-052, 2021.
- Meyer, B., W.K.C. Mok, and J.X. Sullivan. 2015. "Household Surveys in Crisis." *Journal of Economic Perspectives*. American Economic Association. vol. 29, no. 4 (Fall): 199–226.
- Piketty, T., E. Saez, and G. Zucman. 2018. "Distributional National Accounts: Methods and Estimates for the United States." *Quarterly Journal of Economics* 13 (2).
- Saez, E. 2017. "Taxing the Rich More: Preliminary Evidence from the 2013 Tax Increase," *Tax Policy and the Economy* 31, pp. 71–120