Real-Time Inequality*

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Abstract

This paper constructs high-frequency and timely income inequality, wealth inequality, and distributional growth statistics for the United States. Our methodology combines a wide array of administrative data to distribute the official monthly and quarterly US national accounts from the bottom 50% to the top 0.01%. This allows us to compute the rate at which income grows for each group of the population in a way consistent with macroeconomic growth numbers, and to track the distributional impacts of government policies during and in the aftermath of recessions in real time. We test and successfully validate our methodology by implementing it retrospectively back to 1976. Analyzing the Covid-19 pandemic, we find that all income groups recovered their pre-crisis pretax income level within 20 months of the beginning of the recession. By contrast, during the Great Recession of 2008–2009, it had taken four years for average pretax income to recover its pre-crisis level, but 11 years and 10 months for the bottom 50%. A given trajectory of GDP growth is thus compatible with widely different income dynamics for the working class. In the aftermath of the Covid-19 recession, the recovery was strong for the bottom 50% (+ 11.7% in average real pretax income between 2020 and 2021) and the top 10% (+ 9.0%) relative to the middle 40% (+ 5.1%). After accounting for taxes and cash transfers, real disposable income for the bottom 50% was 20.3% higher in 2021 than in 2019. Wealth grew strongly for all groups but wealth concentration increased markedly, to its highest level post-World War II. All estimates are available at `http://realtimeinequality.org` and are updated with each monthly and quarterly release of the national accounts, within a few hours. *JEL* Codes: E01, H2, H5, J3.

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1 Introduction

A major gap in the economic statistics of the United States is the lack of timely estimates of inequality. Thanks to a sophisticated system of national accounts, official macroeconomic data are published almost in real time: quarterly gross domestic product statistics are released less than a month after the end of each quarter; monthly personal income within a month. These statistics, scrutinized by the business community, are a vital input for the conduct of monetary and fiscal policy. But they do not contain information about the distribution of income. While we know how GDP evolves quarterly, we do not know which groups of the population benefit from this growth and which benefit less from it (or potentially not at all). This gap in economic statistics limits the ability of governments and central banks to design effective policies, especially in crisis situation and in the aftermath of recessions.

Our paper attempts to address this gap by creating real-time distributional national accounts. Starting with the official high-frequency national income and financial accounts of the United States, we distribute these macroeconomic aggregates across the population. This allows us to estimate income and wealth inequality monthly and quarterly on a timely basis. Whenever quarterly GDP growth is released, we can compute the rate at which income has grown for each group of the population, from the bottom 50% to the top 0.01%, in a way that is consistent with macroeconomic growth. Following a recession, our series can be used to estimate "distributional output gaps", that is the extent to which income remains below its pre-recession level or trend for the bottom 50% of the distribution, the next 40%, and the top 10%. Finally, since our series incorporate all taxes and government transfers, they allow one to study how national income is redistributed month-to-month and quarter-to-quarter—for example whether fiscal policy enacted after a crisis manages to mitigate income losses for the working class. Our estimates, available online at `http://realtimeinequality.org`, are updated with each monthly and quarterly release of the national accounts, within a few hours.

A key impetus for this project is the Covid-19 pandemic. The pandemic dramatically affected the US economy and led to large-scale government intervention, with federal government annual deficits of around 15% of GDP in both 2020 and 2021, the greatest as a share of the economy since World War II. There is clear evidence that by the beginning of 2022 the economy had on aggregate largely recovered from the shock. But have all groups of the population returned to their pre-pandemic income levels? Is inequality higher or lower after the pandemic than before? If inequality rose, is the rise the largest of the last 10 years, 20 years, 50 years? And to what extent have government policies enacted during the crisis—such as the Paycheck Protection

Program and pandemic unemployment insurance—been successful at mitigating this rise?

Addressing these questions is difficult because datasets with micro-level information on income available at a high frequency are incomplete. The Current Population Survey captures less than half of US national income and, because it excludes certain forms of income (such as employment fringe benefits and business profits) and does not capture the wealthy well (due to top-coding limitations, small sample sizes, and income under-reporting). This large gap with total national income makes it hard to decompose macroeconomic growth. Income tax data are the canonical source used to capture the top of the distribution, but they are only available with a lag of almost two years, due to late tax returns filings by top earners and processing times at the Internal Revenue Service. This lag makes it hard to compare income dynamics for the middle class and for the rich in a timely manner.

To overcome these limitations, we develop a methodology to project inequality at a high frequency on a timely basis. We start with the annual distributional national accounts micro-files of Piketty, Saez and Zucman (2018), updated in Saez and Zucman (2020b), that allocate annual national income, household wealth, and more than 100 of their components across the distribution. Taking moving averages of current and adjacent-year micro-data, or using the latest file (2019) for the years 2020 and 2021, we re-scale each component of national income and household wealth to its monthly or quarterly seasonally-adjusted aggregate value. We estimate month-to-month changes in the distribution of labor income (which accounts for about two-thirds of national income) using high-frequency wage data from the Bureau of Labor Statistics Quarterly Census of Employment and Wages by 6-digits NAICS industry × county × ownership sector, monthly employment from the Bureau of Labor Statistics, and weekly unemployment insurance claims from the Department of Labor. For wealth and capital income components, we assume that within-component distributions are unchanged in the short term. For government transfers, we simulate the distribution of new programs (e.g., pandemic unemployment insurance) using program parameters and eligibility rules.

We test and successfully validate our methodology in two main ways. First, building on the important work of Lee (2020), we show that the Quarterly Census of Employment and Wages can be used to predict changes in wage inequality remarkably well. The share of wages earned in the top 1% of industries × counties × ownership sector with the highest average wage (e.g., securities brokerage in Manhattan (which is New York county), Internet publishing and broadcasting in Santa Clara county) is strongly correlated with the share of wages earned by the top 1% individuals. This allows us to project high-frequency changes in wage inequality reliably. Second, we apply our methodology retrospectively back to 1976 and compare predicted to observed income changes across the distribution. We find that we correctly anticipate whether income is growing or falling 95% of the time for the top 1%, 90% for the next 9%, 95% for the next 40%, and 70% for the bottom 50% (which often has negligible income growth over our sample period).

The intuition for why our methodology delivers reliable results is the following. In the short run, the impact of capital income of income inequality is mostly driven by changes in the relative size of the various components of capital income—such as corporate profits and housing rents—as opposed to changes in how each of these components are distributed across the population. Our method, which assumes stable distributions within component but captures changes in their aggregate values, is thus well-suited to estimating the short-term impact of capital income on the distribution. For labor income, short-term changes in distributions can be large, as unemployment spikes in recessions. But in contrast to capital income, for components of labor income we do not assume stable distributions: we successfully capture high-frequency distributional changes thanks to the quasi-real time Bureau of Labor Statistics wages and employment statistics.

Using our newly constructed data to examine the Covid-19 pandemic yields three main findings. First, all groups of the population recovered their pre-crisis pretax income levels within 20 months of the start of recession, which began in March 2020. The recovery for the working class was dramatically faster than during the previous economic downturn—the great recession that started in December 2007—during which it had taken 11 years and 10 months for the bottom 50% to recover its pre-crisis, pre-tax-and-transfer income level. For adults in the lower half of the income distribution, whose income had experienced little growth before taxes and transfers since the beginning of the 1980s, income before government intervention rose 11.7% in 2021. The recovery was also strong for the top 10% (+ 9.0%), relatively less so for the middle 40% (+ 5.1%).[1] Second, changes in government programs during the pandemic further boosted the disposable income of the bottom 50%. After accounting for taxes and cash and quasi-cash transfers, disposable income for adults in the bottom 50% was 20.3% higher in 2021 than in 2019. Economic impact payments, unemployment insurance, and an expanded

[1] All growth numbers in this article are adjusted for inflation using the official national income deflator. The same deflator is used for all groups of the population. Average annual income per adult grew 7.6% in 2021 in our series, faster than gross domestic product per adult (+5.4%). As explained in Section 3.1.2 below, although the two numbers should conceptually be nearly identical, in practice they can diverge because income and output are estimated using largely independent data sources, creating a statistical discrepancy which can be non trivial when estimating short-term growth. Section 5.1 provides a detailed discussion of income dynamics during the Covid-19 pandemic.

child tax credit lifted disposable income for the working class. Third, wealth grew strongly for all groups but wealth concentration increased markedly. The share of wealth owned by the top 0.1% adults (with wealth equally-split among married spouses) increased 1.3 point from the last quarter of 2019 to the last quarter of 2021, to reach 19.1%. Wealth concentration at the end of 2021 was its highest level in the post-Word War II era. The share of income earned by the top 1% adults was also at its highest level in 2021 on a pre-tax-and-transfer basis, but it was below its peak after taxes and government transfers.

At the outset it is worth stressing a number of limitations of our work. First, we take the national accounts as given. The methodology to estimate quarterly GDP and monthly income has been refined over decades and the estimates embody rich information from administrative data sources, but they are imperfect, particularly the early releases upon which we rely to create our inequality statistics for the most recent quarter. Looking forward, high-frequency estimates of GDP growth could be improved by incorporating private sector data (Chetty et al., 2020), thus improving our ability to track inequality in real time. In the meantime, we follow the national accounts in updating our series when revised estimates of quarterly GDP are published.[2] Second, our real-time distributional national accounts focus on income and wealth groups; they lack information on gender, race, location, occupation, and other relevant dimensions of socio-economic inequality. We view our paper as a prototype of real-time inequality statistics, a prototype that could be refined, enriched, and eventually incorporated into official national account statistics as more information becomes available at a high-frequency and estimation techniques are refined.[3]

The rest of this paper is organized as follows. In Section 2 we relate our work to the literature. Section 3 presents our methodology. Section 4 tests and validates our methodology by implementing it retrospectively. In Section 5 we apply our methodology to the Covid-19 pandemic and discuss the results. Section 6 concludes.

[2]The first estimate of quarterly GDP is available near the end of the first month after each quarter. A second estimate is released about a month after, and a third and final estimate about a month after the second estimate, i.e. about three months after the end of the quarter.

[3]On the wealth side, the Federal Reserve has already created Distributional Financial Accounts, distributing aggregate household wealth at the quarterly frequency (Batty et al., 2019). On the income side, the US Bureau of Economic Analysis has a long existing program of distributing personal income from national accounts and has also explored how to create higher frequency inequality statistics (Fixler, Gindelsky, and Kornfeld, 2021). This project has greatly benefited from discussions with the both the Fed and the BEA teams.

2 Related Literature

2.1 Previous Attempts at Estimating Inequality at a High Frequency

There has been and there are ongoing efforts to estimate inequality at a high frequency in the United States.

The Federal Reserve of Atlanta maintains a monthly wage growth tracker, constructed using microdata from the Current Population Survey following a methodology developed in Daly et al. (2011).[4] The tracker reports the median percent change in the hourly wage of employed individuals observed 12 months apart. Breakdowns by, e.g., wage quartiles, gender, occupation, and census divisions are shown. The wage quartile series provide valuable information on the dynamics of wages across the distribution. Their main limit is that they do not account for non-workers, hence do not map onto overall income inequality. During recessions, the median wage of employed workers in the bottom quartile often rises as low-wage workers are laid off; even though bottom wages may appear to be growing relatively fast, inequality may in fact be rising. Another limitation is that the data are top-coded at $150,000 in annual wage, roughly the 95^{th} percentile of the wage distribution. They miss the dynamic of income in the top 5%, a group that earns about a quarter of all wages. In contrast to the Atlanta wage growth tracker, our work includes non-workers, top earners, and all other forms of income beyond wage income (e.g., capital income and transfer income), making it possible to distribute all of national income and to decompose its growth.

Since 2019, the Federal Reserve has published Distributional Financial Accounts (DFA), distributing aggregate household wealth at the quarterly frequency (Batty et al., 2019). Following the prototype wealth inequality statistics constructed in Saez and Zucman (2016), the DFA allocate the official Federal Reserve Financial Accounts totals across the population. In contrast to Saez and Zucman (2016) who primarily rely on income tax data for this allocation, the Federal Reserve uses the Survey of Consumer Finances, a triennal survey of about 6,000 families. As detailed in Section 5.3, the evolution of wealth inequality is consistent in these two projects. Our value-added is to capture the top of the distribution all the way to the top 0.01% (while the top group considered in the DFA is the top 1%), to provide longer time series (back to 1976, while the DFA starts in 1989), and to have more distributional information at the annual frequency (due to the annual nature of tax data, as opposed to the triennal nature of the Survey of Consumer Finances).

[4] See `https://www.atlantafed.org/chcs/wage-growth-tracker`.

Recently, Fixler, Gindelsky, and Kornfeld (2021) build on the existing annual distributional personal income statistics created by the Bureau of Economic Analysis (Fixler et al., 2017) to explore the feasibility of a quarterly distribution of personal income. In contrast, we distribute monthly and quarterly national income, the aggregate used to compute macroeconomic growth.[5] There are also a number of methodological differences in the two approaches. Fixler, Gindelsky and Kornfeld (2021) rescale the annual personal income totals component by component to match the corresponding quarterly totals, but do not attempt to project changes in distributions within components. They do not use the Quarterly Census of Employment and Wages to estimate changes in wage inequality, a key step to capture the dynamic of inequality over the business cycle.[6] Their main micro-data is the Current Population Survey, not individual tax return data, making it impossible to provide estimates for the top. They do not average adjacent annual micro-data, sometimes leading to discontinuities at the beginning of new years. These differences notwithstanding, both projects share the same objective of creating timely inequality statistics consistent with the national accounts. Our work was inspired by discussions with staff of the Bureau of Economic Analysis and the ongoing dialogue between academics and researchers within government agencies is in our view highly valuable.

2.2 Impacts of the Covid-19 Pandemic on Inequality

Our work also relates to the literature on the impact of the Covid-19 pandemic on inequality, most recently surveyed in Stantcheva (2022). The literature emphasizes the equalizing effects of large-scale government intervention in high-income countries, while suggesting several channels through which the pandemic may, once these interventions fade out, eventually widen economic disparities. Relative to this body of work, our main contribution is to provide a general methodology that can be applied to all business cycles and could be implemented throughout the world. The main feature of our methodology is its comprehensive character (capturing 100% of national income), timeliness (estimates are available within a month on `http://realtimeinequality.org`), and granularity (with estimates available from the bottom 50% to the top 0.01% for pretax income, posttax income, disposable income, and wealth). Applied to the Covid-19 crisis, our methodology delivers new insights, such as the fast recovery

[5]See Saez and Zucman (2020) for a discussion of the differences between these two concepts and their implications.

[6]We agree with Fixler, Gindelsky, and Kornfeld (2021) that a simple methodology based on the re-scaling of aggregates shows reasonable results during stable growth years but significantly underestimates inequality during and in the aftermath of recessions. A value-added of our work is to demonstrate that a more sophisticated methodology—using high-frequency wage and employment statistics—can overcome this issue.

of working class incomes even before government intervention; the relatively slower growth of middle-class incomes; and the sharp contrast between the dynamics of working-class incomes during this crisis and the preceding economic downturn.

3 Methodology to Estimate Inequality in Real Time

In this section we outline the main concepts and methodology we use to distribute US national income and household wealth at the quarterly and monthly frequency. All the data sources and computer code we use are available online at `realtimeinequality.org`; here we focus on the main steps of the methodology and key conceptual issues.[7] The data are currently constructed using solely publicly available data sources. Conceivably, estimates could be refined using non-public additional data either from government (such as tax statistics) or from the private sector (as in Chetty et a. 2020). Because we want our estimates to be updated frequently and for the foreseeable future, using solely public sources is preferable.

3.1 Definitions and Construction of Aggregate Income

3.1.1 Income Concepts

Our goal is to distribute seasonally-adjusted quarterly and monthly income aggregates corresponding to the income concepts studied in Piketty, Saez and Zucman (2018) and in the distributional national accounts literature (Blanchet et al., 2021): factor income, pretax income, posttax income, and disposable income.

Factor income is the income earned from labor and capital, before any tax and government spending and before the operation of the pension system. Pretax income is factor income after the operation of the pension system and disability and unemployment insurance (public or private). Contributions to pensions (including Social Security taxes) and to unemployment and disability insurance are removed, while the corresponding benefits are added. Posttax income is pretax income minus all taxes (other than Social Security taxes, already subtracted from pretax income), plus all government transfers (other than Social Security and unemployment benefits, already included in pretax income) and the government deficit. Factor, pretax, and posttax income all add up to national income. National income is the most comprehensive notion of income: it includes all income that accrues to resident individuals, no matter the

[7]Methods to estimate the distribution of household wealth and national income at the annual frequency are presented in Saez and Zucman (2016) and Piketty, Saez and Zucman (2018). A discussion of the general issues involved in creating annual distributional national accounts and general guidelines are presented in Alvaredo et al. (2016), updated in Blanchet et al. (2021).

legal nature of the intermediaries through which this income is earned. In particular, and in contrast to personal income, national income is not affected by business decisions to operate as corporations vs. non-corporate businesses such as partnerships, a decision influenced by the tax system. This feature of national income maximizes comparability over time. National income is computed following internationally-agreed conventions and methods, maximizing comparability across countries. Our focus on national income is in line with recommendations made by the Stiglitz, Sen and Fitoussi (in 2019) Commission on the Measurement of Economic Performance and Social Progress.

National income is closely related to GDP, the aggregate most often used to compute economic growth. National income is GDP minus capital depreciation plus net income received from abroad.[8] Since capital depreciation and net foreign income account for a relatively small fraction of GDP and are not volatile, the growth of national income is conceptually nearly identical to the growth of GDP. In practice, because GDP and national income are estimated using largely independent sources in the United States, their growth can diverge; see Section 3.1.2 below.

Factor income—the sum of income from labor and capital, the two factors of production—naturally lends itself to decompositions of economic growth. Pretax income and posttax income include income which is socialized through social insurance and the tax-and-transfer system. At the individual level, the growth of pretax and posttax income thus reflects both output growth and changes in transfers. Comparing the growth of posttax income to the growth of factor income provides a comprehensive view of the extent to which taxes and government spending equalize growth across the distribution.

We also consider a fourth income concept, disposable cash income. It is equal to pretax income minus all taxes, plus all cash or quasi-cash (e.g., food stamps) transfers. In contrast to posttax income, disposable cash income excludes in-kind government transfers such as Medicare and Medicaid, collective consumption expenditures, and the government deficit. Disposable income does not add up to national income and thus cannot be used to decompose economic growth. It is, however, a useful concept to approximate the income that individuals have at their disposal to consume and save; by subtracting the saving component, it can be used to study consumption inequality. Disposable income is a particularly useful concept to transparently study the distributional impacts of government stabilization policies during economic crises.[9]

[8] In other words, US national income is the income generated by labor and capital supplied by US residents, in the United States and abroad, net of capital depreciation.

[9] In periods of crisis, posttax income—which includes government spending other than cash transfers but adds

3.1.2 Construction of Monthly and Quarterly Income Aggregates

To construct aggregate factor, pretax, disposable, and posttax income, we use the monthly and quarterly national accounts published by the Bureau of Economic Analysis, starting from the most detailed components of personal income (published monthly) and domestic product and income (published quarterly). All the monthly and quarterly aggregates we use are seasonally-adjusted.

Factor income is obtained as the sum of wages and salaries, supplements to wages and salaries, proprietor's income, rental income, corporate profits, interest income, and production taxes, minus production subsidies, non-mortgage interest payments, and government interest payments.[10] In our monthly micro-files described below, the distribution of each of these components is estimated. Three remarks are in order. First, factor income is estimated using the income approach of the national accounts. As is well known there is a statistical discrepancy between gross domestic income (GDI) and gross domestic product (GDP) in the US national income and product accounts (e.g., Fixler, de Francisco and Kanal, 2021). We do not allocate the statistical discrepancy. Thus our estimates match income growth, not product growth; in years when the statistical discrepancy is not zero, we do not exactly capture GDP growth. Second, corporate profits are not available at the time the first estimate of quarterly GDP is released, but with a one-month lag. For the last quarter of our series (currently the fourth quarter of 2021), we impute corporate profits so that quarterly GDP growth equals quarterly GDI growth.[11] Third, some components of factor income—taxes on production, subsidies on production, and corporate profits—are available quarterly but not monthly. In that case we disaggregate the quarterly series using Denton's (1971) method, following the International Monetary Fund (2017) recommendations to compile quarterly national accounts.

Pretax income is obtained as factor income minus private pension contributions, Social Security taxes, and contributions to unemployment insurance; plus private pension benefits, Social Security benefits, and unemployment insurance benefits. Importantly, pretax income captures the effect of expanded unemployment insurance during the Covid-19 pandemic (and

back the government deficit—can be lower than disposable income. This was the case in the second quarter of 2020, due to the massive federal deficits induced by the economic response to the Covid pandemic. Disposable income has two advantages relative to posttax income in this context. First, it does not require one to make (necessary uncertain) assumptions about who bears the burden of the government deficit. Second, it is more directly informative of the consumption possibilities of households and of the extent to which government policies manage to smooth them over the business cycle.

[10] Mortgage interest payments are already subtracted from rental income. Government interest is not part of national income.

[11] This approach minimizes bias and variance relative to an alternative approach assuming that corporate profits grow like GDP in the last quarter.

also subtracts in a distributionally neutral way the deficit created by the large expansion of unemployment benefits). To construct disposable and post-tax income, we subtract other social insurance contributions (i.e., Medicare taxes), direct taxes, the estate tax, and add veteran benefits, other cash benefits, and for posttax income Medicare, Medicaid, other in-kind transfers, collective expenditures, and the government deficit. Social insurance contributions and benefits, as well as most government taxes and transfers, are published monthly as part of personal income. As with factor income, when an item is not available at the monthly frequency (e.g., collective government expenditure), we disaggregate it using Denton's (1971) method.

3.2 From Annual to Quarterly and Monthly Income Distributions

We construct monthly synthetic micro-files in which lines represent synthetic individuals and columns correspond to the income concepts and their components mentioned above. The unit of observation is the adult individual, defined as an individual aged 20 or more. Unless otherwise noted, all the statistics we report in this paper are for "equal-split adults," defined as individual adults with income and wealth equally split between married spouses. On `http://realtimeinequality.org`, we also report statistics at the household level, where a household is a tax unit as defined by the tax code, i.e., either a single person aged 20 or above or a married couple, in both cases with children dependents if any.

We use these monthly files to estimate the distribution of what annual income would be if seasonally-adjusted monthly income aggregates and their distributions remained stable over 12 months.[12] Another way to measure inequality at a high frequency would be to estimate the inequality of actual monthly income. Because of income mobility, this approach would lead to more inequality at the monthly frequency than at the annual frequency. By contrast, our procedure which annualizes income makes inequality statistics comparable at high vs. low frequency.[13] It is consistent with the way the national accounts work, which show monthly and quarterly income on an annual basis.

To construct our monthly files, the starting point is the annual distributional national accounts synthetic micro-data of Piketty, Saez and Zucman (2018), updated in Saez and Zucman (2020b). From that baseline we proceed in three steps: (i) we convert these files to the monthly

[12] Quarterly income is computed as the average of monthly income over the three months of the quarter.

[13] If one wanted to study the inequality of actual monthly income, income mobility could be controlled for by following households over time. There is, however, no micro-data in the United States allowing to track the longitudinal evolution of household income month after month or quarter after quarter (Fixler, Gindelsky and Kornfeld, 2021). Our approach that focuses on monthly and quarterly distributions of annualized incomes does not require longitudinal data and usefully by-passes this issue.

frequency; (ii) we incorporate external information on the month-to-month evolution of the distribution of wage income and other income components; and (iii) we rescale all components to their monthly values to match the seasonally-adjusted national accounts aggregates.

The Piketty, Saez and Zucman (2018) micro-files combine IRS tax micro-data, surveys, and national accounts data to construct annual distributions of income and wealth consistent with national accounts. Since their first publication, a literature has developed to test assumptions, conduct robustness tests, develop improvements, and maximize comparability with other countries where similar methods are followed (Blanchet et al., 2021). The current files, comprehensively revised component-by-component, incorporate the results of this body of work. Saez and Zucman (2020b) present the key features of these updates,[14] as well as a detailed reconciliations with other estimates of US income and wealth inequality. The last annual micro-file, which also incorporates the latest national accounts revisions, is for the year 2019, the latest for which distributional income tax data are available and the year immediately preceding the Covid-19 pandemic. This file serves as our baseline for 2020 and 2021 estimations.

In the first step of our methodology, we convert these annual files to the monthly frequency. To do so we normalize the population and the distribution of each income and wealth component to one. We then create monthly versions of these files mixing samples from two adjacent years with unequal weights. To create a file corresponding to month m in year y, we combine the micro-data for the year y with its weights multiplied by $m/12$ with the micro-data for the year $y-1$ with its weights multiplied by $1-m/12$. Therefore, each monthly file is a moving average of the yearly files over the last twelve months. This procedure smoothes out short-run, year-specific, mean-reverting variations, which are not informative of the distribution for a given month, and would otherwise introduce discontinuities in the series.

3.3 Projecting Changes in the Distribution of Labor Income

The second—and most important—step of our methodology involves incorporating external information on the month-to-month evolution of the distribution of labor income. We estimate both changes in the extensive margin (number of employed vs. non-employed individuals, including recipients of unemployment insurance benefits) and in the intensive margin (changes in the wage distribution).

[14] A complete log of all updates since initial publication is available at `http://gabriel-zucman.eu/usdina`, as are current micro-files, computer code, and tabulations of key findings. All vintage releases and corresponding code are also published.

3.3.1 Number of Wage Earners and Unemployment Insurance Recipients

To capture changes in the extensive margin, we adjust the number of wage earners and unemployment insurance (UI) recipients to match estimates constructed from the Bureau of Labor Statistics and Department of Labor data. Specifically, we estimate the number of workers using the Bureau of Labor Statistics (BLS) monthly release of non-farm employment at the national level. Since the number of employed people in a given year is mechanically higher than in a given month, we adjust monthly employment numbers to make them commensurable with yearly estimates from Internal Revenue Service (IRS) tax data, using the linear relationship observed between the BLS and the IRS numbers. We use that adjusted series to disaggregate the yearly employment numbers recorded in the IRS data.

We estimate the number of UI recipients in a given month using the Department of Labor's weekly publication of unemployment claims. We aggregate this data by month and adjust it for seasonal variations using the X11 procedure (Shiskin et al., 1967). The number of UI recipients in a given week is mechanically lower than in a given year. To get an estimate commensurable with yearly inequality levels, we adjust the number of UI claims by a constant coefficient to match the annual levels recorded in the IRS tax data. We then use this series to disaggregate yearly unemployment claims using Denton's (1971) method.

We rank individuals according to the distribution of wages or UI benefits and attribute a salary or a UI benefit only to the top $p\%$ of observations, where p is the percent of people that we estimate receive wages or UI benefits. One challenge with that approach is ranking observations that receive no wage or no UI benefits. If $p\%$ of the population is employed, then the rank of the $1 - p\%$ of people who received no salary is unknown, and all we know is that it lies somewhere between zero and $1 - p\%$. To overcome this issue, we run an interval-censored regression model of the rank against the position in the distribution of factor, pretax, and post-tax disposable income. Based on this model, we simulate a rank for observations with no wage or UI benefits. This approach is a simple way of ensuring that, when we extend the support of wage income or UI benefits, the people who receive that new income are similar to those already receiving it.

3.3.2 Wage Distribution

To project the monthly distribution of labor income (for employed individuals), we use the Quarterly Census of Employment and Wages (QCEW). Starting from observations in the updated Piketty, Saez and Zucman (2018) micro-data that we estimate receive positive wage income, we divide these observations into percentiles, and attribute the wage value calculated from the

QCEW data to each of these percentiles. Together with the previous step for non-workers, this approach ensures that we preserve the copula (i.e., the joint distribution of ranks) between labor and other types of income as measured in the Piketty, Saez and Zucman (2018) micro-files. We now present the QCEW data and explain how we compute wage distributions in this dataset.

BLS's Quarterly Census of Employment and Wages. The QCEW is an administrative dataset published quarterly by the BLS, which records employment levels and wages for workers covered by State unemployment insurance laws and Federal workers covered by the Unemployment Compensation for Federal Employees program (about 95% of the workforce). The QCEW is highly disaggregated: it provides employment counts and average wages within cells that correspond to a given county, industry, and type of ownership (i.e., public or private). The data records industries at the 6-digit NAICS level, distinguishing about a thousand different industries. As a result, the sample contains about a million observations in recent years, much more than a typical micro-level wage survey.

The QCEW reports employment counts monthly but reports wages at a quarterly frequency. This is not a significant issue since wages are sticky, so changes in the wage distribution in the short run are driven by changes in the relative employment of low-wage and high-wage workers rather than by changes in their respective salaries. We run the wage data in the QCEW through a moving average of the last twelve months to get smooth monthly wages and to get rid of the seasonality in the wage data (due, for example, to end-of-year bonuses). In cases where this procedure introduces missing values, we impute them back using a regression of the logarithm of wages against county, time, industry, and type-of-ownership fixed effects.

Estimating the Distribution of Wages in the QCEW. We build upon the pioneering work of Lee (2020) who constructed quarterly wage income distributions using the QCEW data. We use the QCEW as if it were a micro-level dataset, treating each cell as an observation whose weight is the employment count and whose value is the average wage. We remove outliers, defined as cells whose wage is less than half of a full-time minimum wage job. We then estimate the average wage by percentile in each month.

We correct seasonal variations (introduced by seasonality in employment numbers) by running the average wage for each percentile through the X11 procedure. The resulting monthly series are smooth and their trends follow the tax data closely. Because the QCEW data is aggregated, it understates the level of inequality. We fix this by conducting a simple adjustment to the monthly series. Specifically, we regress the tax data wage against the QCEW wage for each percentile and use the prediction from these regressions as our monthly estimate for each percentile. This procedure works well because the relationship between the average wage of a given percentile in the QCEW data and the tax data is strongly linear. Importantly, this correction does not vary with time and thus does not weaken the predicting power of the QCEW data. The final adjusted series closely track the level and trend of the tax data.

Compared to the most recent macroeconomic data, the QCEW is available with a lag of one to two quarters. We use the BLS State and Metro Area Current Employment Statistics to fill this gap. These statistics are similar to the QCEW. The main difference is that they are based on a survey of about 144,000 businesses and government agencies rather than on administrative data. As a result, they are available quicker and released every month, albeit with a coarser level of aggregation (about 19,000 monthly series covering up to 300 industries and 450 areas, compared to about a million series in the QCEW). We match each QCEW cell to three Current Employment Statistics series. The first matches the location of the QCEW cell as precisely as possible, the second matches it at the state level, and the third at the national level. Because there is a trade-off in the Current Employment Statistics series between the level of geographical and industry disaggregation, using those three series allows us to extract as much information as possible. We average the trend from these three series in each cell and use this average trend to extend the QCEW data in the most recent quarters.

3.4 Projecting the Distribution of Capital Income and Wealth

For capital and mixed income, we proportionally rescale each component to match aggregate, seasonally-adjusted monthly values. The components of capital and mixed income we consider are proprietor's income, rental income, corporate profits, interest income, and interest payments. We assume that the distribution of each component is unchanged at a high frequency, but take into account the change in the relative size of each component, which is the first-order driver of short-run changes in the concentration of capital income. From the second to the third quarter of 2020, for example, corporate profits grew 25% while rental income was little changed. Since corporate profits are more concentrated than housing rents toward the top of the distribution, income inequality rose, which our procedure captures.

We follow the same methodology to construct quarterly wealth distributions. The macroeconomic aggregates that we distribute come from the official Financial Accounts published by the Federal Reserve. These accounts are published every quarter, which is why we construct wealth aggregates at a quarterly frequency only. Household wealth is the sum of tenant-occupied housing, owner-occupied housing, S-corporation equity, C-corporation equity, equity in non-corporate businesses, fixed-income assets, and pension assets, minus tenant-occupied mortgages, owner-occupied mortgages, and non-mortgage debt. Wealth inequality is estimated in the updated Piketty, Saez and Zucman (2018) micro-files by updating each of these wealth component to its end-of-quarter value. Following Saez and Zucman (2016), our estimates exclude unfunded pensions (such as promises of future Social Security benefits), consumer durables (which are not assets in the System of National Accounts and thus excluded from wealth in other countries; see United Nations, 2009), and the assets and liabilities of non-profit institutions such as private foundations.

3.5 Government Transfers

We simulate the key components of the government response to the Covid crisis. Three programs warrant special treatment: the Paycheck Protection Program, Covid relief payments, and the expanded refundable tax credits.

The Paycheck Protection Program is a loan program designed to keep small businesses afloat, representing about $1,000 billion, or 5% of national income. The government forgave most of these loans, assuming companies kept their employees and wages stable. Following Autor et al. (2022), we distribute 70% of the program's expenditures to business owners and the remaining 30% to wage earners. We construct a novel estimate of the program's distributional effect for the incidence on wages. We use the publicly available data on each loan, which we match to the QCEW data based on the date of the loans, the industry, and the location of the business. We manage to match about 5,700,000 loans to 5,500,000 QCEW cells. We estimate both an extensive margin (fraction of the workforce covered) and an intensive margin (fraction of the wage bill covered) for each percentile of the labor income distribution, which we use to simulate the effect of the Paycheck Protection Program on workers.

Second, we allocate the three waves of Covid relief payments ("economic impact payments") based on program rules using taxable income as reported in the updated Piketty, Saez and Zucman (2018) files.

Third, we also allocate the expanded refundable tax credits (child tax credit and earned income tax credit) based on income and eligibility using our micro-data.

4 Validation Tests

This Section provides a number of validation test of our methodology to project high-frequency income distributions.

QCEW wage distribution prediction. First, we examine how well the QCEW data can predict the actual wage income distribution. Figure 1 compares the wage distributions in the annual micro distributional national account data and those obtained in our monthly synthetic distributional national account data using the QCEW as described above. Each panel depicts the share of total wage income earned by a specific fractile (bottom 50%, middle 40%, next 9%, and top 1%) among individuals with positive wage income. The QCEW adjusted data track the annual micro-data very closely for all groups. This means that our methodology to predict the wage distribution using the QCEW is generally accurate. These results are consistent with the pioneering analysis of Lee (2020) who first used the QCEW to create quarterly wage distributions for macro-business cycle analysis.

Retrospective validation methodology. Our long time series since 1976 allow us to check retrospectively whether our projections using prior year micro-data combined with current year data (national accounts, employment figures, QCEW wage distributions, etc.) provide accurate distributional estimates. We proceed as follows. For each year t from 1976 to 2018, we start from year t annual micro-data and we use our methodology retrospectively to age the year t data into a year $t+1$ synthetic annual micro-data using solely the external sources of national income statistics macro aggregates, employment and unemployment aggregates, and the QCEW for year $t+1$. We can then compute any distributional statistic with this synthetic micro-data for year $t+1$ and compare them with the actual statistics coming out of the actual micro-data for year $t+1$. To test whether the predictions for year $t+1$ are accurate, we focus on changes from year t to $t+1$ where year t is always estimated using the actual micro-data while year $t+1$ is estimated using the projected synthetic micro data vs. the actual micro-data.

Predicting undistributed corporate profits. Figure 2 depicts the predicted growth (x-axis) vs. the actual growth (y-axis) in yearly undistributed corporate profits accruing to the top 1% income earners and expressed in percent of total national income from year t to year $t+1$ for each year from 1976 to 2019. The dots align along the 45 degree line showing that our predicted growth is generally highly informative of actual growth. The reason why prediction is so accurate is because the year-to-year changes in the share of corporate profits accruing to the top 1% are small relative to the year-to-year changes in aggregate corporate profits. For example, corporate profits can fall by 20% or more year-to-year during a recession and then soar back up during a recovery. As a result, changes in aggregate corporate profits drive short-term distributional effects, and hence our method using macro-aggregates works very well to project the distributional impact for such a component.

Overall prediction. Next, we examine whether our methodology is successful at predicting overall changes in the income distribution. We focus on annual growth rates by income group and the top 1% income share which are crucial distributional statistics.

Figure 3 focuses on annual growth rates by broad income group: the bottom 50%, the next 40%, the next 9%, and the top 1%. It depicts the predicted growth rate (x-axis) vs. the actual growth rate (y-axis) in yearly real income per adult from year t to year $t+1$ for each year from 1976 to 2019. Each panel depicts a specific income group. Years for which there is a significant tax reform that generates income shifting (for tax avoidance reasons) and often distorts reported incomes are depicted with a red triangle). The linear fit is close to the 45 degree line showing that our predicted growth is generally highly informative of actual growth.

Figure 4 focuses on the annual change in the top 1% income share. It depicts the predicted change in the top 1% income share (x-axis) vs. the change in the top 1% income share (y-axis) from year t to year $t+1$ for each year from 1976 to 2019. Years for which there is a significant tax reform that generates income shifting (for tax avoidance reasons) and often distorts reported top incomes are depicted with a black triangle). Overall, in 80% of years, our predicted change has the correct sign, showing that our predicted change is generally highly informative of the actual change in the top 1% income share.

5 Inequality During the Covid-19 Pandemic

This Section uses our real-time estimates to analyze the dynamics of income and wealth across the distribution during the Covid-19 pandemic. We start by studying the dynamic of income before government intervention, then move to disposable income and wealth.

5.1 The Dynamic of Factor Income During the Covid-19 Recession

Dynamic across the income distribution. The Covid-19 pandemic led to a dramatic collapse in average income. Between February 2020 (the last month before the recession) and

April 2020 (the trough of the recession), annualized real US national income per adult fell 15.2%, the largest decline observed in our series during any period of time. Average income then rebounded sharply.

Figure 5 shows the dynamic of factor income across the distribution during this crisis at the monthly frequency. To contrast the collapse in income during the pandemic with normal income dynamics, the graph starts in July 2019. As the figure shows, the economic downturn caused by the pandemic led to the strongest income declines for the working-class and to a lesser extent for the top one percent. It affected the middle-class and upper-middle class relatively less. Factor income collapsed -32.7% for the bottom 50% between February 2020 and April 2020. The fall was less severe for the middle 40% and the next 9% (a decline of about 10%), because individuals in these groups that were more likely to remain employed and keep their wage. It was very large for the top 1% (-18.6%), due to the collapse of business profits, a key source of income at the top.

The groups that had the largest losses in 2020 had the largest gains in 2021. On average, real annual factor income per adult grew 7.6% in 2021, but it increased 11.7% for the bottom 50%—by far the highest annual income growth rate for this group since the start of our series in 1976—and 12.7% for the top one percent. Growth was lower for the middle 40% (+5.1%). As already noted, our methodology distributes national income, not domestic product. Although income and product growth should conceptually be nearly identical, in practice they can diverge because income and output are estimated using largely independent data sources. This is the case in currently available national accounts statistics for 2021: according to official GDP statistics, gross domestic product per adult grew +5.4% in 2021, less than income per adult (+7.6%). This gap may shrink when revised GDP and income estimates are published, and suggests that currently available headline GDP statistics may understate the strength of the recovery.

According to our estimates, all groups of the income distribution recovered their pre-crisis income level within 20 months, but not at the same pace. It took 13 months for average income to recover its February 2020 level. The groups least affected by the crisis recovered first; the most affected ones recovered last. The middle 40% and the next 9% recovered their pre-crisis income level in the last quarter of 2020. The top 1% recovered in January 2021, 10 months after the beginning of the crisis. The bottom 50% recovered in October 2021, 20 months after the beginning of the crisis. Because the bottom 50% was hit the hardest and recovered last, the pandemic, had, by the end of 2021, exacerbated factor income inequality. The share of factor income earned by the bottom 50% was 11.4% in December 2021, less than in 2019. The share of factor income earned by the top 1% adults was 19.5%, its highest level in the post-World War II era.[15]

Comparing the Covid-19 and Great Recession recessions and recoveries. During the Covid-19 crisis, the recovery for the working class was dramatically faster than during the previous economic downturn, the Great Recession that started in December 2007. Figure 6 contrasts the evolution of average factor income per adult and bottom 50% factor income during the Great Recession and the Covid crisis. Income is normalized to 100 in the month preceding each recession. A number of striking findings emerge.

First, and as already largely documented, for the economy as a whole the recovery from the Covid-19 crisis (13 months) was much faster than the recovery from the Great Recession (4 years and a month). Second, in the aftermath of the Great Recession, it had taken a staggering 11 years and 10 months for the bottom 50% to recover its pre-crisis factor income level. From 2010 to 2016, a period during which the economy rebounded and crossed its pre-crisis output level, the bottom 50% experienced virtually no growth: average factor income for that group stayed constant at about $16,500 per adult (in constant $2021). Income started growing in 2017 and only exceeded its December 2007 level in October 2019, just a few months before the Covid-19 pandemic. The slow recovery of the working class is a notable and robust feature of the Great Recession.[16]

By contrast, factor income for the bottom 50% immediately and sharply rebounded in the aftermath of the Covid-19 pandemic. By the time average income had recovered from the Great Recession (January 2012), bottom 50% income was still 12% below its pre-crisis income level; it experienced no growth, and would flatline for five more years. By the time average income had recovered from the Covid-19 crisis (March 2021), the bottom 50% was booming and within a few months would exceed its pre-crisis income level. A given trajectory of GDP growth is thus compatible with widely different market income dynamics for the working class.

[15] Similar findings are obtained when looking at annual income in 2021 (instead of annualized December 2021 or annualized 2021Q4 income). For the bottom 50%, average 2021 annual income remained below its 2019 level (-1.2%). Other groups, which were less hit by the initial shock and recovered faster, had higher average factor income in 2021 than in 2019: +2% for the middle 40%, +3.9% for the top 10%, +4.4% for the top 1%.

[16] Quantitatively similar results are obtained when restricting to the working-age population, or looking at pretax income, i.e., after the operation of the pension system. The stagnation of factor income for the bottom 50% in the aftermath of the Great Recession is not an artifact of population ageing; it reflects the stagnation of wages for the bottom 50% during this period of time. The top fiscal income shares of Piketty and Saez (2003), which have been used to study the fraction of growth accruing to top income groups (see Saez, 2008, and subsequent updates), also revealed the unequal recovery from the Great Recession.

Figure 7 shows the dynamic of the top 1% during the two recessions. During both the Great Recession and the Covid-19 recession, income initially fell more for the top 1% than on average. But the recovery was faster. As average income returned to its pre-crisis level, income in the top 1% grew faster than average. In the medium run both recessions thus ended up increasing factor income concentration.

5.2 The Effects of Government Intervention

Government intervention during recessions affects the distribution of growth, sometimes massively. In 2021, for the United States as a whole, real disposable income per adult was 9.7% higher than in 2019. Disposable income grew much faster than national income (+2.5%), due to massive government deficits.

The bottom 50% most benefitted from the increase in government spending. After accounting for taxes and cash and quasi-cash transfers, average disposable income for adults in the bottom 50% was 20.3% higher in 2021 than in 2019. Figure 8 shows a step-by-step decomposition of the effect of government intervention on the income of the bottom 50%. To facilitate the interpretation of the results, we focus on the working-age population (aged 20 to 65) and we always rank by factor income so that all figures for a given month refer to the same group. The graph reveals the relative importance of the various government programs enacted during the pandemic.

In the early months of the crisis, the Paycheck Protection Program lifted incomes. But given available evidence on the incidence of the program (Autor et al., 2022), the effect appears small. According to our estimates, the Paycheck Protection Program increased the average monthly income of the bottom 50% of the working-age population by about $100. It replaced only about a fifth of the decline in factor income that occurred in the first months of the crisis for this population (from about $1,500 in February 2020 to about $1,000 in April and May 2020). Unemployment insurance, which was significantly extended during the crisis, had much larger effects, lifting average bottom 50% monthly income by about $400 in May, June, and July 2020, and by up to $200 a month through to the summer of 2021.

The three waves of Covid-relief payments (April 2020, January 2021, and March 2021) had large but temporary effects on monthly income. Disposable monthly income for the bottom 50% peaked in March 2021 as a result of the third payment, to reach $3,200— twice as much as before the pandemic ($1,600). By the end of 2021, disposable monthly income for the bottom 50% had declined to $2,000. Virtually the only reason why disposable income was higher for the working class in the end of 2021 than before the pandemic was the expanded child tax credit and the expanded earned income tax credit for adults with children.[17]

5.3 The Rise of Wealth Concentration

Finally, we study the effect of the Covid-19 crisis on wealth inequality. Figure 9 shows the dynamic of wealth across the distribution from the first quarter of 2019 to the last quarter of 2021. Wealth grew strongly for all groups but wealth concentration increased markedly. From the end of 2019 to the end of 2021, average real wealth per adult grew 22.6%. For the top 0.1% the increase was 31.8%, and for the top 0.01% it reached 36.2%. As a result, the share of wealth owned by the top 0.1% adults (with wealth equally-split among married spouses) increased 1.3 point from the end of 2019 to the end of 2021, to reach 19.1%—the highest level recorded in the post-Word War II era.

The rise in wealth concentration observed during the Covid pandemic is comparable—if anything slightly larger—to the rise observed during the Great Recession, +1.0 point for the top 0.1% wealth share between the end of 2007 and the end of 2010. Recent economic crises thus appear to exacerbate wealth inequality in the United States. However, not all large increases in wealth concentration occur during periods of crisis.The rise in wealth concentration observed in 2020 and 2021 is the second largest increase observed over a period of two calendar years, after the rise seen in 1996 and 1997 (+1.8 point for the share of wealth owned by the top 0.1%), a period of rapid economic growth.

Our findings on the dynamics of wealth inequality are consistent with other existing evidence. First, our series are consistent with the official Federal Reserve Distributional Financial Accounts, both for the Covid-19 crisis and back to 1989, the first year of the DFA. Specifically, from the third quarter of 1989 to the third quarter of 2021, the top 1% wealth share grew 8.5 points in the DFA (vs. +8.1 in our series); the next 9% gained 0.2 point (-0.9 in our series); the middle 40% lost 7.6 points (-6.0 in our series); the bottom 50% lost -1.2 (-1.2 in our series). In both the DFA and our series, wealth concentration increased during the Covid-19 pandemic and the top 1% wealth share was at its highest recorded level at the end of 2021.[18] Second, our

[17] As in the national accounts and the distributional national accounts of Piketty, Saez and Zucman (2018), refundable tax credits—i.e., cash transfers administered through the tax system—are categorized as cash transfers (not negative taxes); thus the child tax credit and the earned income tax credits show up as "regular cash transfers" in Figure 8.

[18] As detailed in Saez and Zucman (2020), top wealth shares are lower in the DFA because in contrast to Saez and Zucman (2016) and this paper, the DFA include unfunded defined benefit pensions and consumer durables (vehicles) in wealth, both of which are relatively equally distributed. Once the same definition of wealth is used, the level, trend, and composition of top wealth shares are identical in the two projects.

findings on the dynamics of top-end wealth are consistent with evidence from real-time Forbes billionaires estimates, which show that the share of total household wealth owned by the top 0.0001% wealthiest households (the 18 richest American tax units today) grew from 1.1% in 2019 to 1.4% in 2021, by far its highest level on record.

6 Conclusion

Macroeconomic growth statistics are not necessarily informative of how income grows for most social groups. Yet government statistics currently available in the United States do not make it possible to know who benefits from economic growth in a timely manner. Our paper attempts to address this gap by creating real-time distributional national accounts: monthly and quarterly estimates of income inequality and wealth inequality, available within a few hours of the publication of official monthly and quarterly national accounts aggregates. We leverage a wide array of administrative data to develop reliable projection methods, which we test and successfully validate by applying our methodology retrospectively back to 1976. Although our estimation procedure appears to deliver reliable results, our estimates could be improved by complementing the administrative data we use with real-time private sector data (Chetty et al., 2020) or with internal government administrative data. We view our real-time statistics as a prototype which we hope will be refined, enriched, and eventually incorporated into official national account statistics. All our estimates are available online at `http://realtimeinequality.org`

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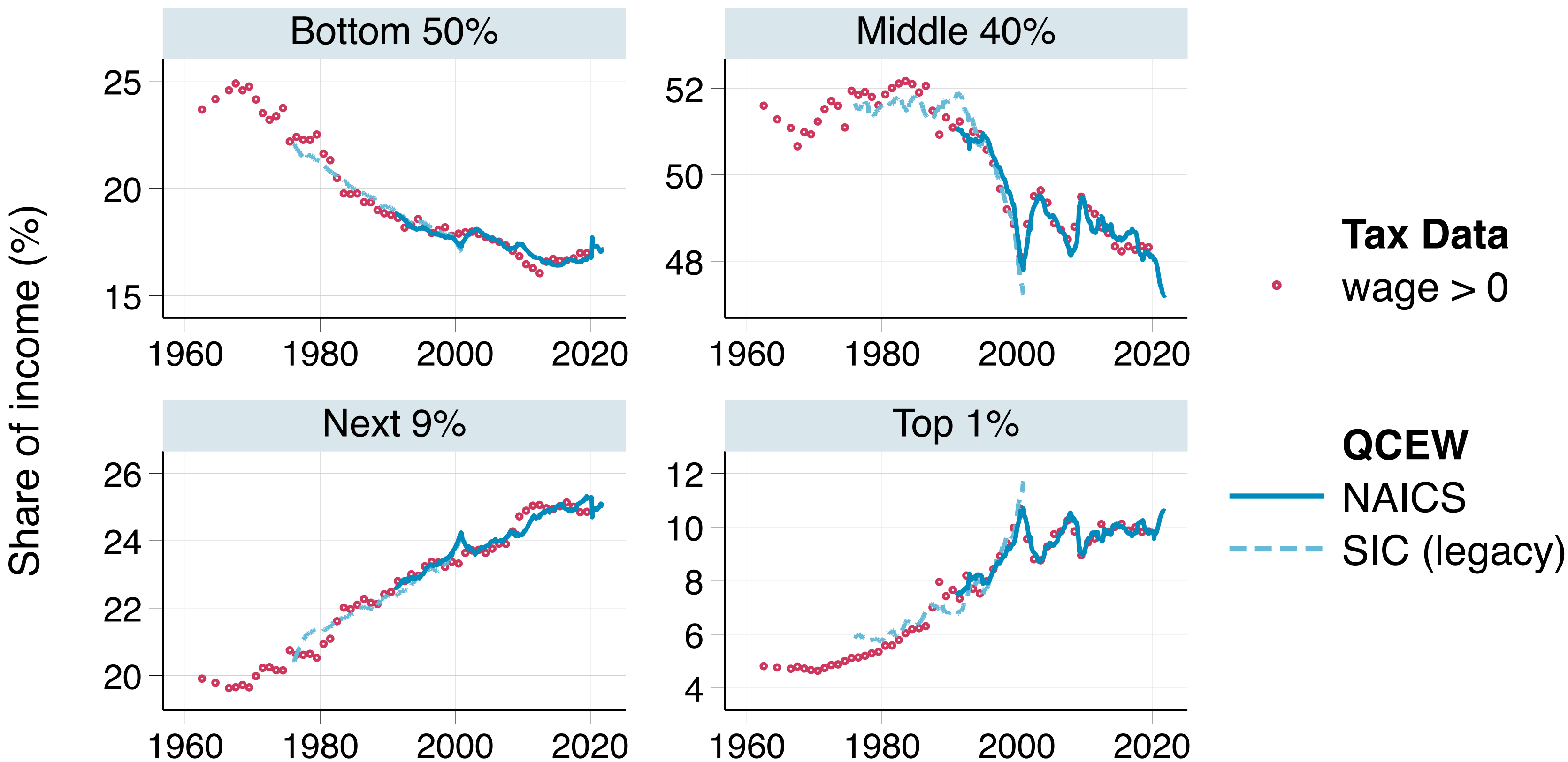
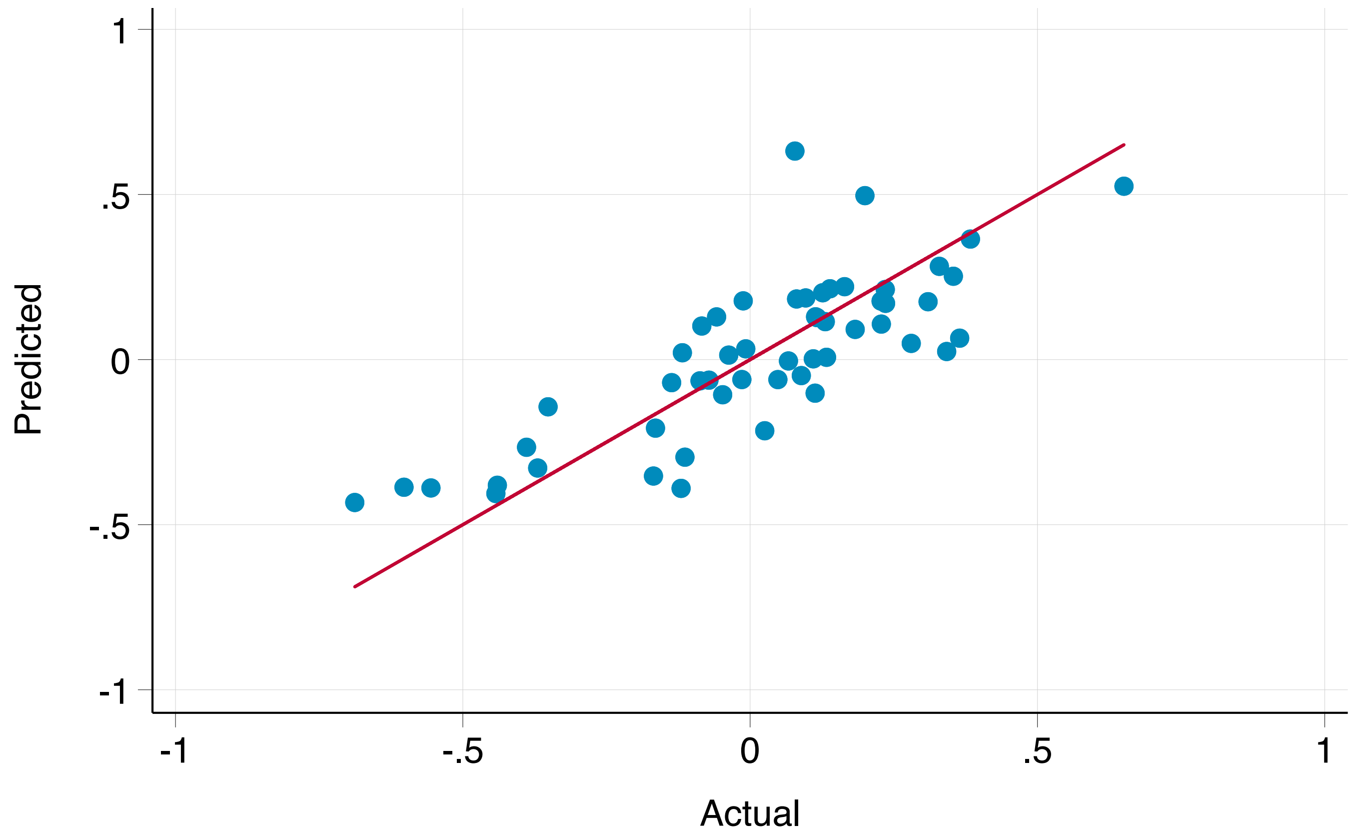
Figure 1: Wage Distributions: Tax Data vs. QCEW



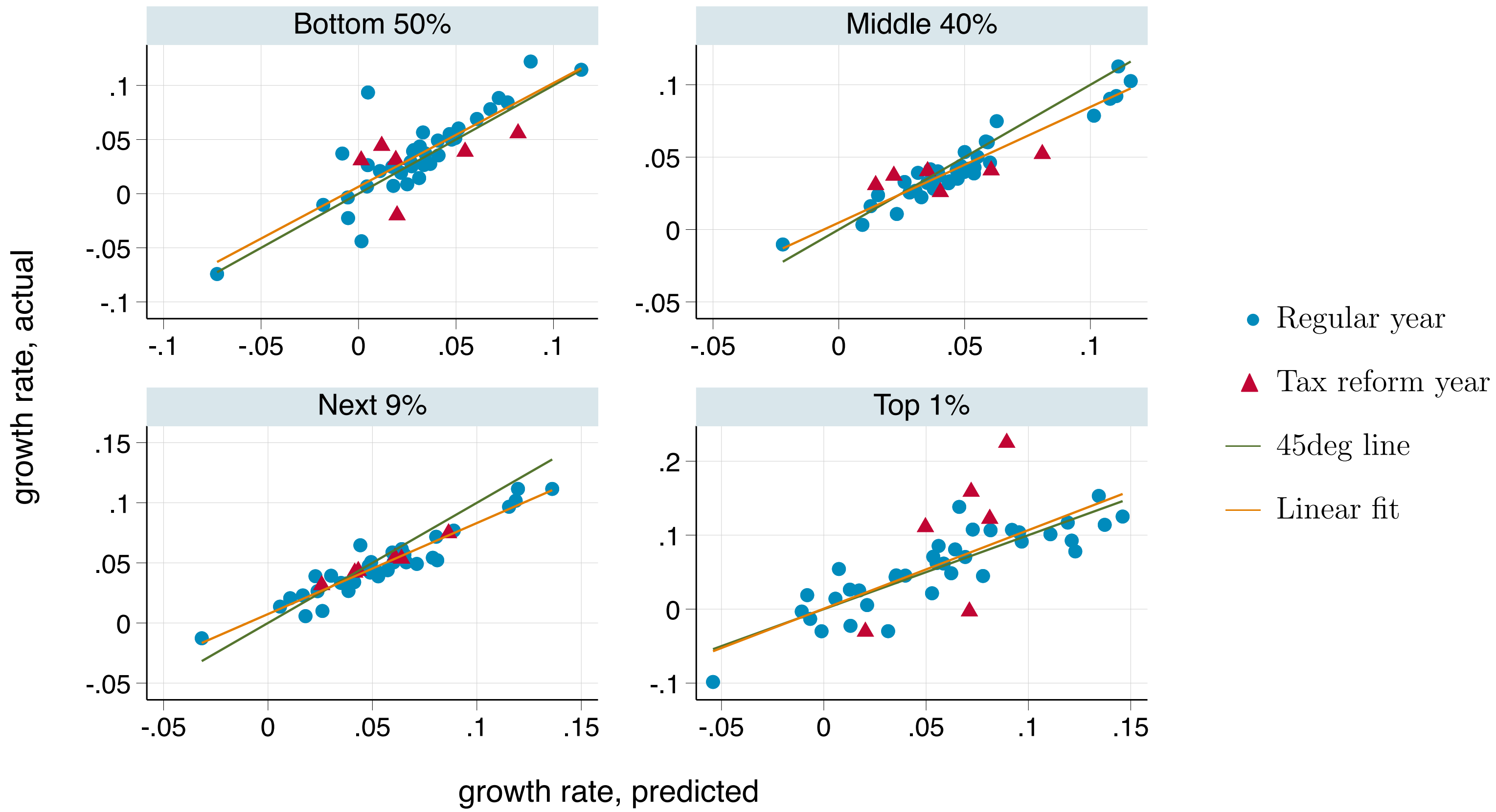
Notes: This figure compares the wage distributions in the annual micro-data of Piketty, Saez and Zucman (2018) and those obtained in our monthly synthetic distributional national account data using the QCEW as described in the text. Each panel depicts the share of total wage income earned by a specific fractile (bottom 50%, middle 40%, next 9%, and top 1%) among individuals with positive wage income. The QCEW-adjusted data track the annual micro-data very closely for all groups.

Figure 2: Undistributed Profits of Top 1%: Predicted vs. Actual



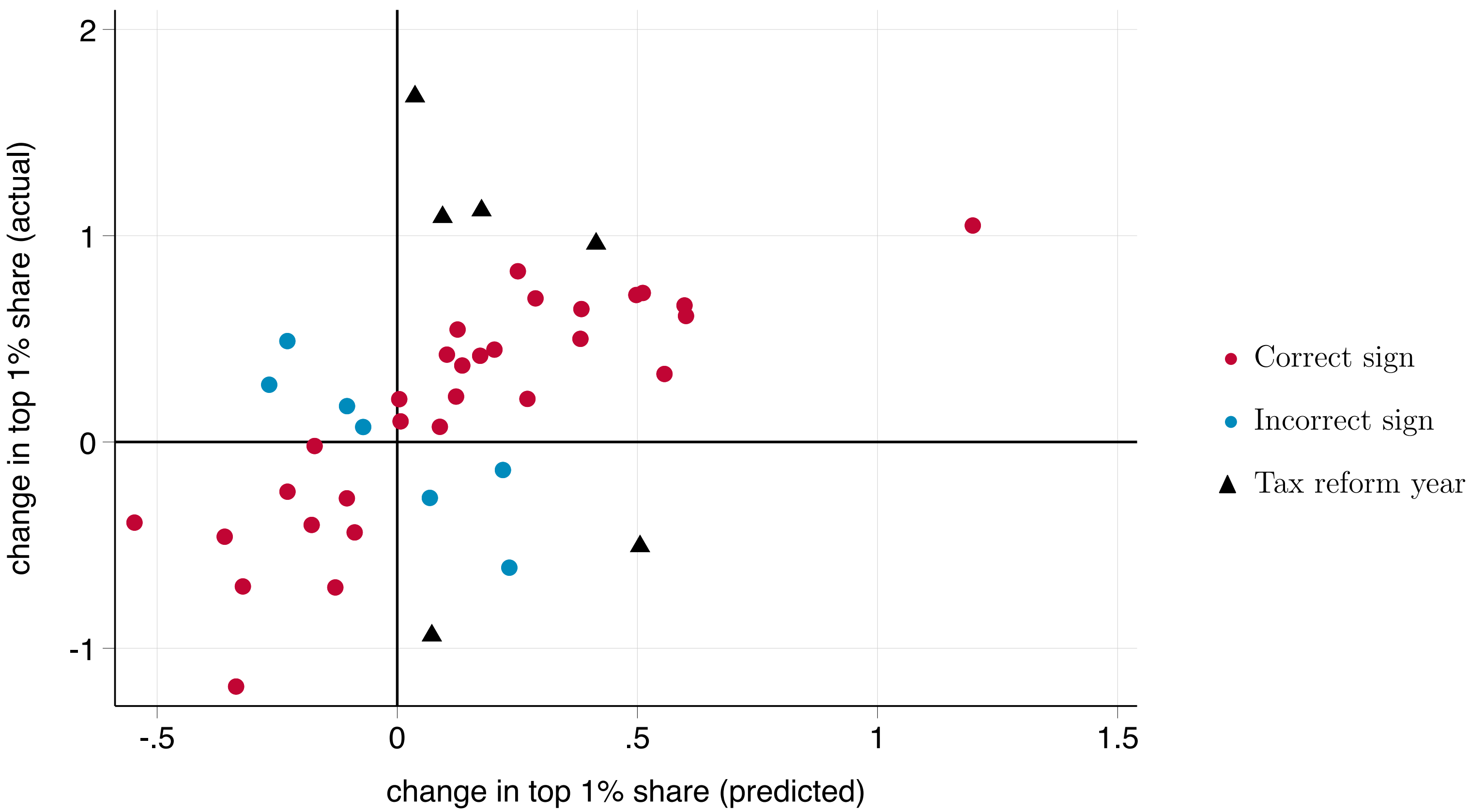
Notes: This figure depicts the predicted growth (y-axis) vs. the actual growth (x-axis) from year t to year $t+1$ in yearly undistributed corporate profits accruing to the top 1% income earners, expressed in percent of total national income for each year from 1976 to 2019. The actual growth is the growth obtained using the annual distributional national account micro-data (finalized data) for both years t and $t+1$. The predicted growth is the growth obtained using the annual distributional national account micro-data (finalized data) for year t and the projected synthetic micro-data for year $t+1$ using our methodology. The dots align along the 45 degree line showing that our predicted growth is generally highly informative of actual growth.

Figure 3: Income Growth Rate: Predicted vs. Observed



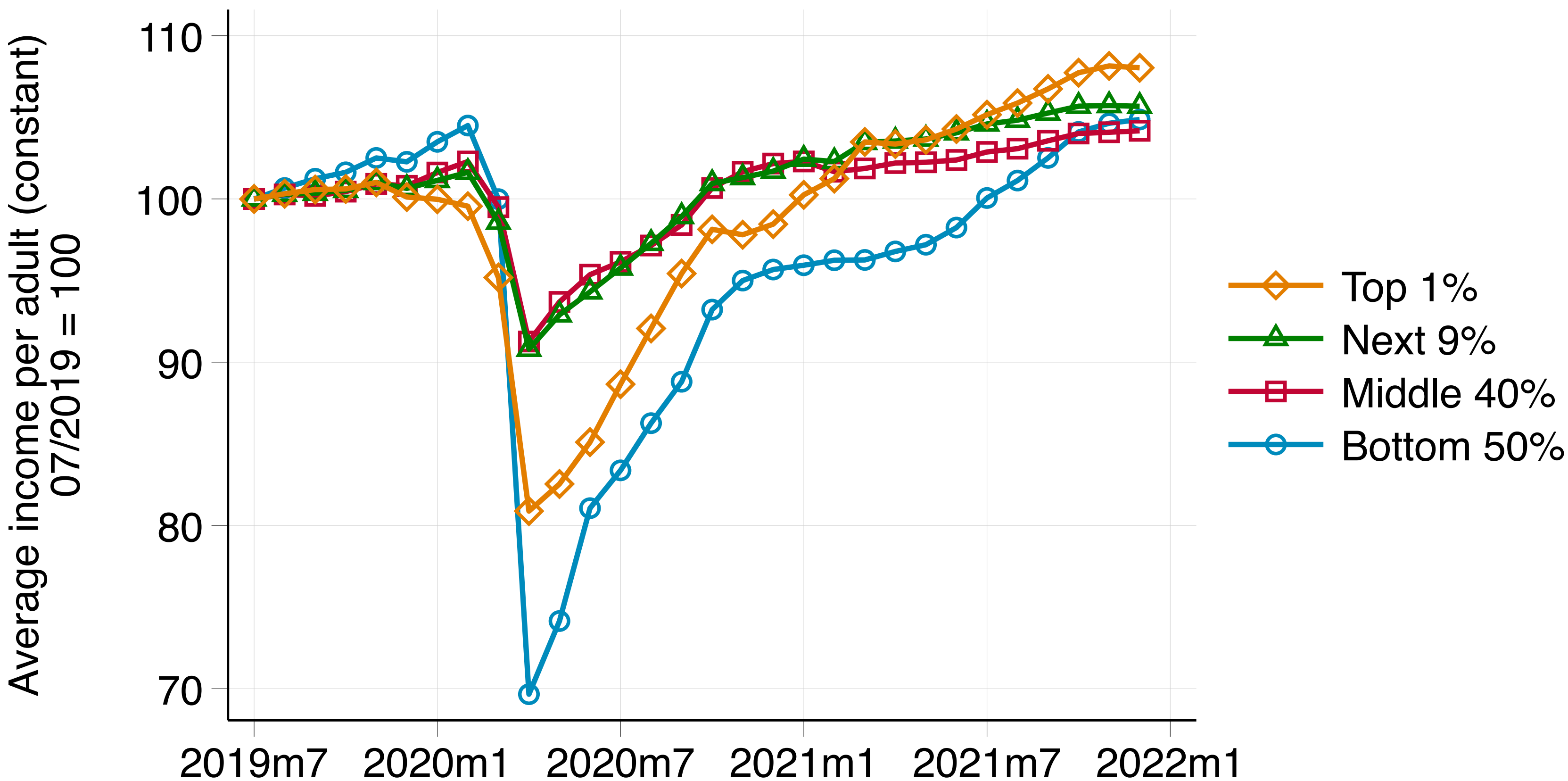
Notes: This figure depicts the predicted growth rate (x-axis) vs. the actual growth rate (y-axis) in yearly real income per adult from year t to year $t+1$ for each year from 1976 to 2019. Each panel depicts a specific income group. The actual growth rate is the growth rate obtained using the annual distributional national account micro-data (finalized data) for both years t and $t+1$. The predicted growth rate is the growth rate obtained using the annual distributional national account micro-data (finalized data) for year t and the projected synthetic micro-data for year $t+1$ using our methodology.Years for which there is a significant tax reform that generates income shifting (for tax avoidance reasons) and often distorts reported incomes are depicted with a red triangle). The linear fit is close to the 45 degree line showing that our predicted growth is generally highly informative of actual growth.

Figure 4: Income Growth Rate for the Top 1%: Predicted vs. Observed



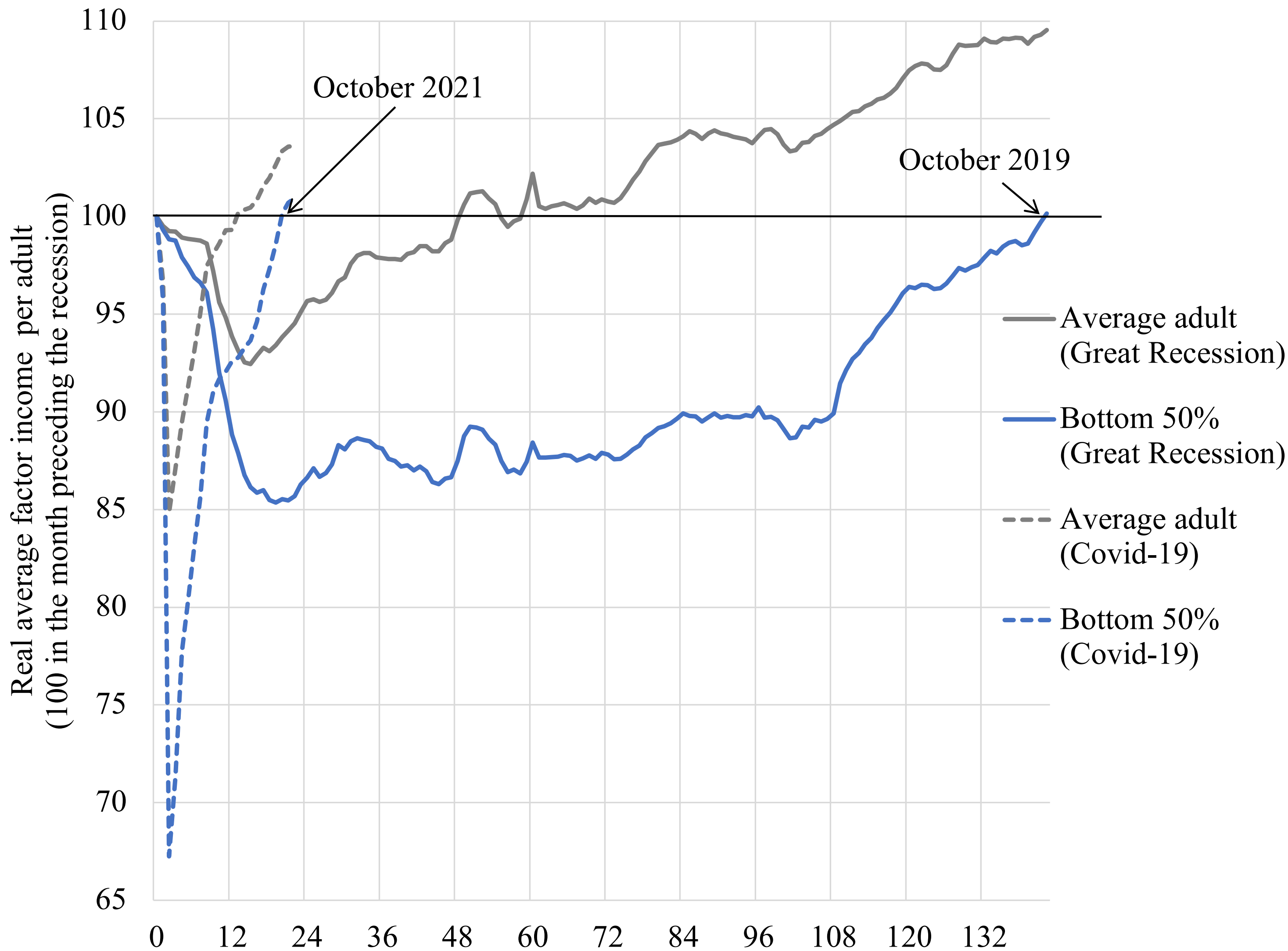
Notes: This figure depicts the predicted change in the top 1% income share (x-axis) vs. the change in the top 1% income share (y-axis) from year t to year $t+1$ for each year from 1976 to 2019. The actual top 1% income share change is obtained using the annual distributional national account micro-data (finalized data) for both years t and $t+1$. The predicted change is obtained using the annual distributional national account micro-data (finalized data) for year t and the projected synthetic micro-data for year $t+1$ using our methodology. Years for which there is a significant tax reform that generates income shifting (for tax avoidance reasons) and often distorts reported top incomes are depicted with a black triangle). Overall, in 80% of years, our predicted change has the correct sign, showing that our predicted change is generally highly informative of the actual change in the top 1% income share.

Figure 5: Real Factor Income During Covid



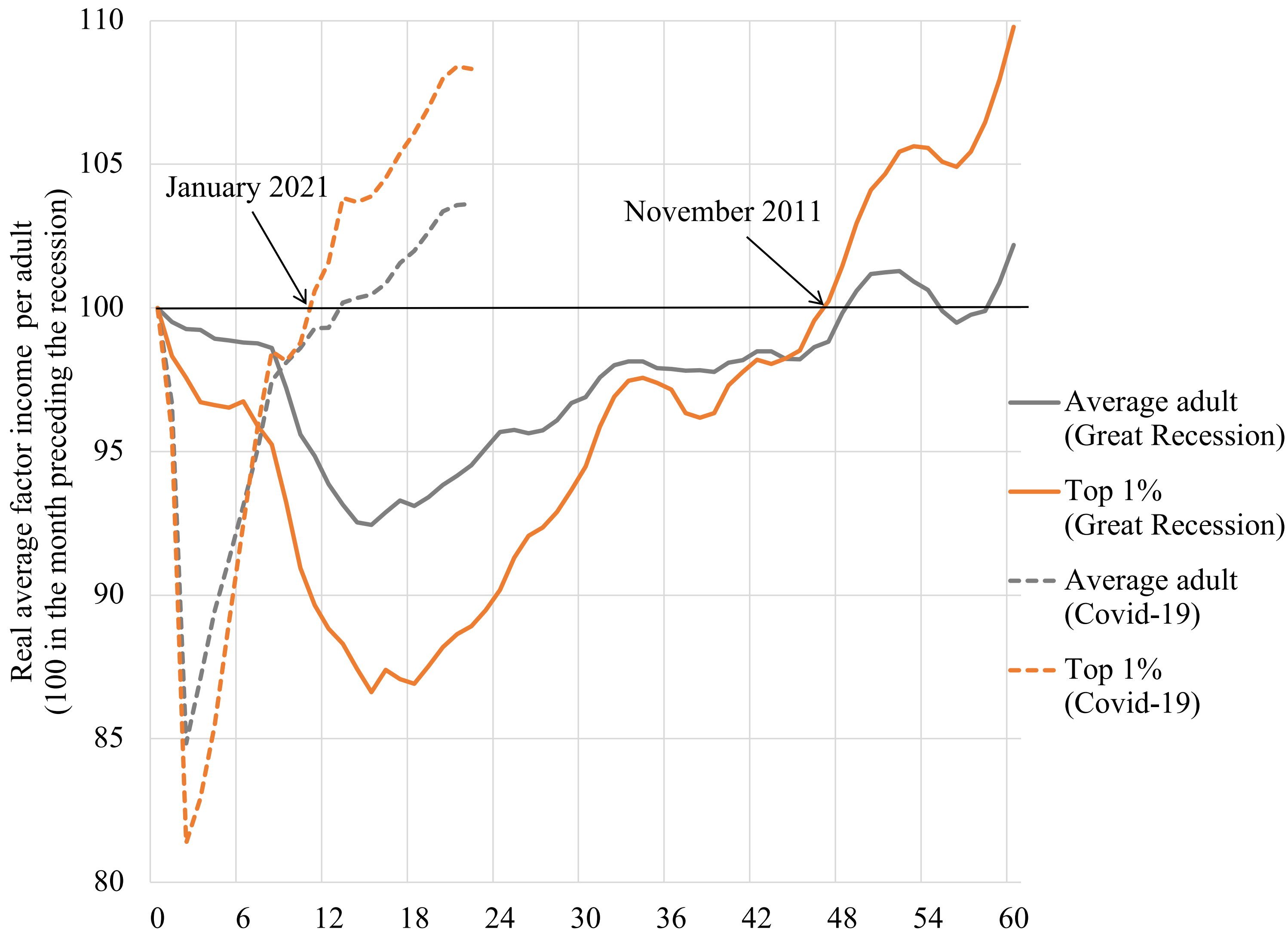
Notes: The figure shows the monthly dynamic of real factor income across the distribution during the Covid-19 recession. The economic downturn caused by the pandemic led to the strongest income declines for the bottom 50% and to a lesser extent for the top one percent. By October 2021 all groups had recovered their pre-crisis income level.

Figure 6: Bottom 50% Income Dynamics During Covid vs. Great Recession



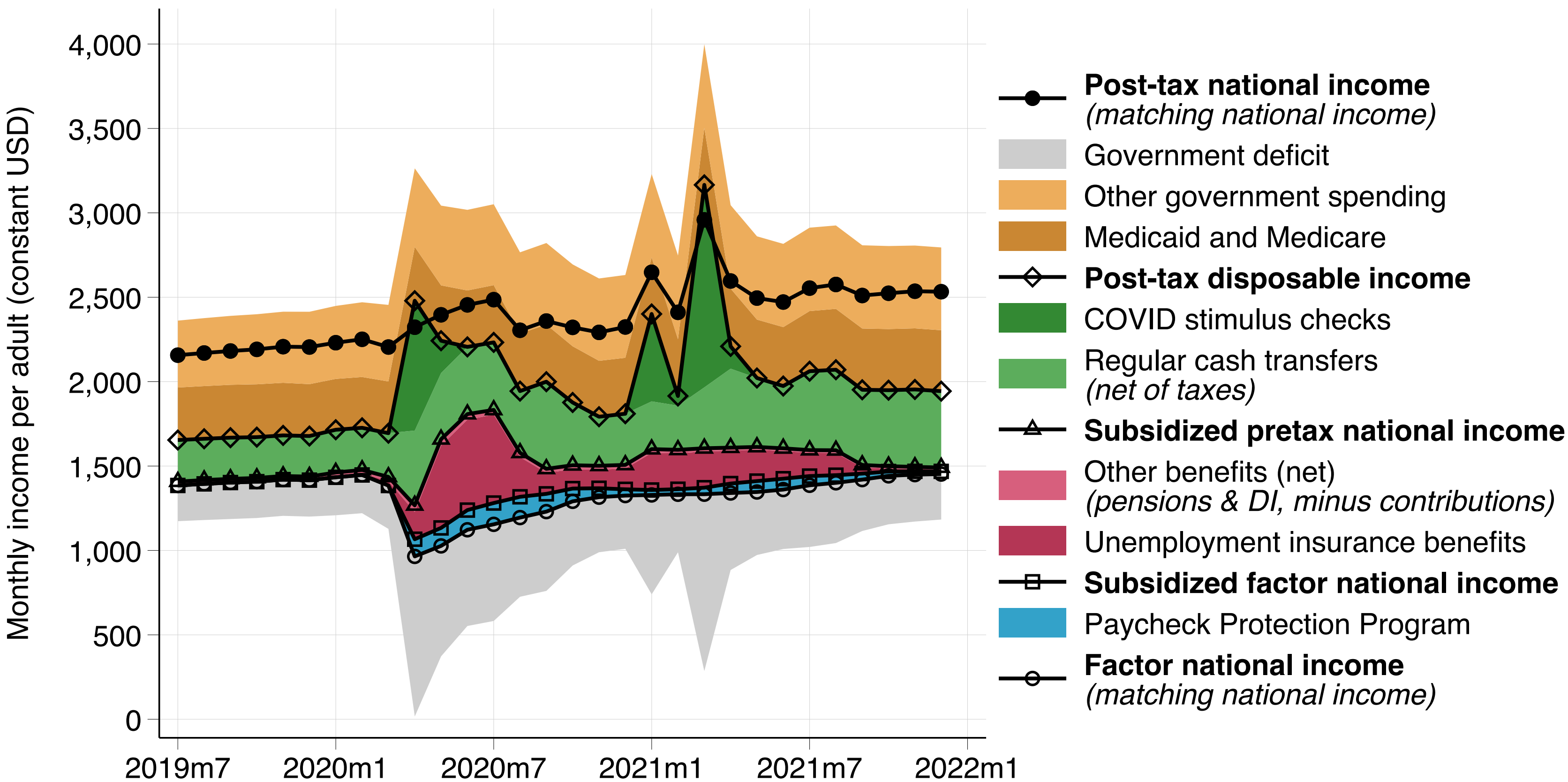
Notes: This figure compares the growth of real factor income per adult on average and for the bottom 50% during the Great Recession and the Covid-19 recession. Income is normalized to 100 in December 2007 for the Great Recession and February 2020 for the Covid-19 recession, corresponding to the month immediately preceding the recession. The x-axis counts the number of months since the start of the recession.

Figure 7: Top 1% Income Dynamics During Covid vs. Great Recession



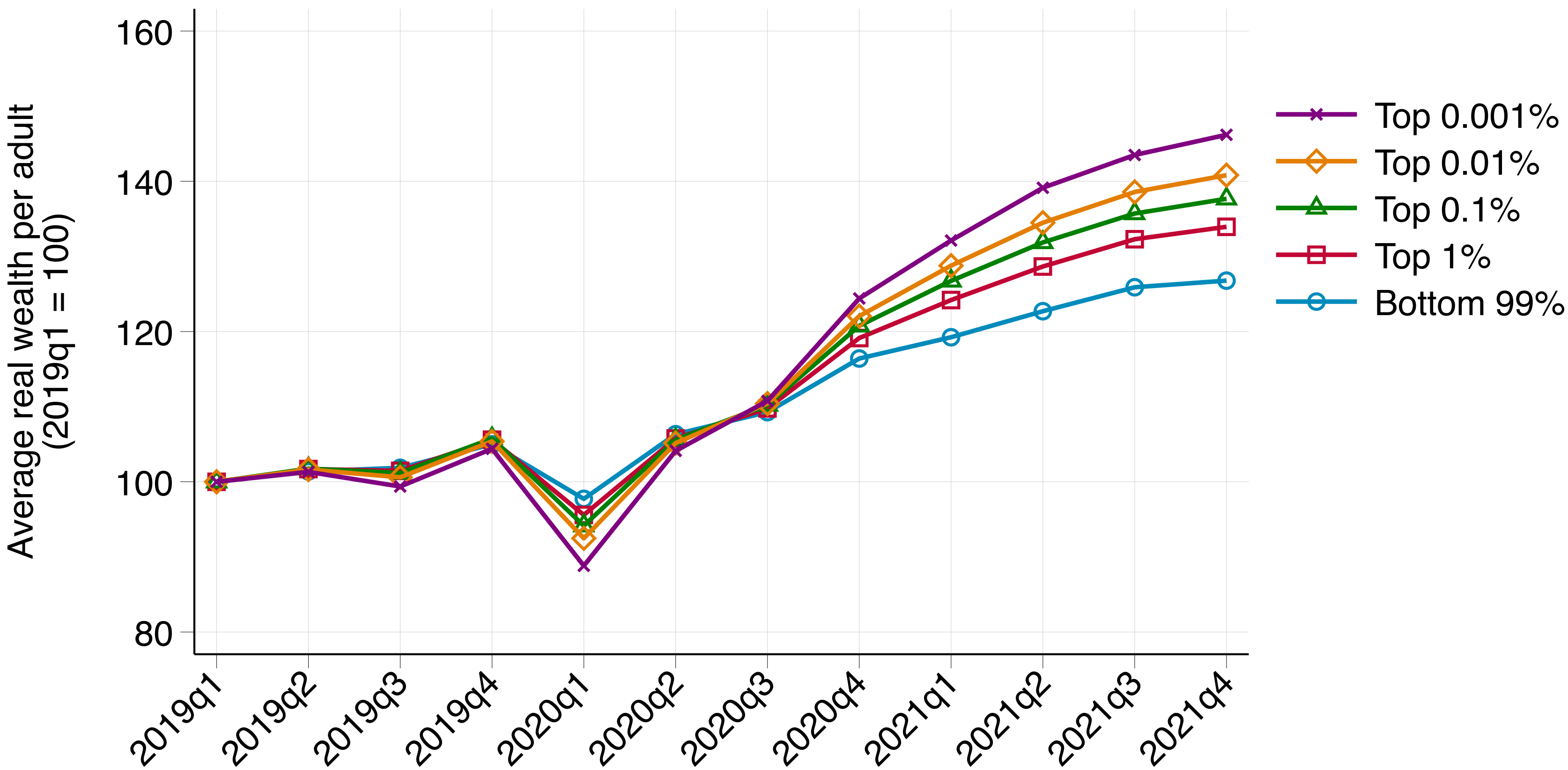
Notes: This figure compares the growth of real factor income per adult on average and for the top 1% during the Great Recession and the Covid-19 recession. Income is normalized to 100 in December 2007 for the Great Recession and February 2020 for the Covid-19 recession, corresponding to the month immediately preceding the recession. The x-axis counts the number of months since the start of the recession.

Figure 8: Income of the Bottom 50% during the Covid Crisis



Notes: This figure decomposes the average real monthly income of the bottom 50% from July 2019 to December 2021. We restrict to the working-age population (aged 20 to 65). Individual adults are ranked by their factor income, and income is equally split between married spouses.

Figure 9: Wealth Inequality During the Covid Crisis



Notes: This figure shows the evolution of real wealth across the wealth distribution from the first quarter of 2019 to the last quarter of 2014. The average wealth of each group is normalized to 100 in the first quarter of 2019. The figure shows, e.g., that the wealth of the top 0.01% increased 40% (adjusted for inflation) from 2019Q1 to 2021Q4.