Income Inequality in the United States

Sean E. Mulholland and Cortnie Shupe

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Abstract

In this paper we investigate the evolution of income inequality in the United States between 1980 and 2016. We find the drivers to be threefold: changes in the labor force composition, changes in household composition, and changes in market return to skills, with the latter two influences dominating this trend. We show that individual real wages grew from 1980 to 2016 throughout the entire wage distribution, indicating that the increase in wage income inequality does not stem from lower real wages at the bottom of the distribution but rather from relatively faster growth in compensation rates of high earners compared to the average earner. We apply a Mata-Machado decomposition to separately identify the contributions of changes in characteristics of workers in the US labor force and changes in returns to these characteristics. The results demonstrate that increasing education levels among the US population as well as increasing returns to education have played a significant role in the growth of wage income inequality, with the role of increasing returns to education dominating. Finally, the paper highlights several common omissions from previous inequality analyses that bias results upward, in particular nonwage compensation and dynamic behavioral responses to taxation incentives.

JEL codes: D3, D63, H2

Keywords: income inequality, labor market, inequality measurement, inequality overview, inequality survey, taxation, wage growth, nonwage compensation

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Introduction

Across the industrialized countries of the Organisation for Economic Co-operation and Development (OECD), income inequality is on the rise (Piketty 2003; Piketty and Saez 2003; Gottschalk and Danziger 2005; Daly and Valletta 2006; Burkhauser et al. 2012; Atkinson, Piketty, and Saez 2011). Despite the high political relevance of the topic, inequality scholars continue to disagree on (1) the appropriate measure of inequality and scope of the problem, (2) the drivers of inequality growth, and (3) the policy implications based on these analyses. The proliferation of research on this topic has led to a need for an overview of the most seminal work on income inequality, highlighting in particular remaining points of contention among experts in the field as well as emerging areas of consensus. This survey seeks to fill that gap.

The current paper focuses on the United States and begins by discussing the challenges associated with measuring inequality. Section 1 weighs advantages and disadvantages of the most commonly applied data sources and how they lead to different measurement strategies for assessing the degree of inequality. This section also outlines important income factors omitted from most inequality analyses owing to data unavailability and considers the likely impact of such omissions on estimates of inequality. Finally, it describes trends in income inequality at the household level in the United States since 1980, both before and after government taxes and transfers, and finds consistent redistribution of approximately 11 percentage points postintervention in comparison to pre-tax-and-transfer inequality throughout the entire period of investigation. Section 2 explores the role of long-run changes to household composition and

marital sorting for household income and inequality. It documents the empirical observation that highly educated people are more likely to marry each other today than in 1980. Moreover, the increasing correlation between the earnings of individuals and their spouses appears to be contributing to the increase in household inequality, such that inequality measures at the household level capture effects not only from resource pooling but also from increasingly homogeneous marriage preferences.[1]

Going beyond the household-level analysis, section 3 attempts to disentangle the drivers of pre-tax-and-transfer individual wages in order to better understand their contribution to growing inequality at the household level. The individual-level analysis shows real wage growth from 1980 to 2016 throughout the entire wage distribution, indicating that the growth in wage income inequality does not stem from lower real wages at the bottom of the distribution but rather from relatively faster growth in compensation rates for high earners than for the average earner. Having established differential growth rates in wages across the distribution, section 4 decomposes this wage growth into effects attributed to changes in the composition of the labor force and changes in the returns to these characteristics. The decomposition exercise shows that increasing education levels among the US population as well as increasing returns to education have played a significant role in the growth of wage income inequality, with the role of increasing returns to education dominating.

Section 5 devotes more detail to the dynamics of nonwage and non-salary compensation, which has increased in importance over time. Specifically, it discusses the failure of pre-tax income inequality measures to account for tax-deferred retirement accounts and nontaxable health insurance compensation, which exaggerates the measured share of income at the top and

[1] In the interest of making apples-to-apples comparisons between 1980 and 2016, household-level data are from male-female marriages only; because same-sex marriages were not legalized nationally until 2015, these marriages are not included in the data for this paper.

underestimates inequality between the lowest deciles of workers who are marginally employed or not employed vis-à-vis better-compensated workers.

In section 6, we turn our attention to recent work on capital income and wealth flows in the United States and the emerging consensus that the increase in measured income inequality among the top 10 percent of earners has been driven by increases in labor income more so than increases in nonlabor income. This observation stands in contrast to most other OECD countries, which have documented a more dominant role of capital income in increasing inequality. Nevertheless, the amount of capital income reported has also increased at the top of the earnings distribution in the United States since 1980. Section 7, however, details the challenges related to linking this observed capital income growth to actual changes in wealth rather than to shifts in reporting wealth as capital versus labor income, as these two possibilities are not observationally distinguishable. Section 8 concludes with a brief discussion of policy proposals that may increase opportunities for those households at the bottom of the income distribution and potentially lower inequality.

Section 1. Measuring Inequality

Income inequality is composed of disparities in both income from labor and income from capital. While individuals often shift their income strategically between these two sources in response to incentives inherent in the tax system, the importance and effect of each component must be considered separately in order to understand the drivers of these trends and developments in their unequal growth.

Accurately measuring labor and capital income flows and wealth inequality faces several challenges: (1) which data to use, (2) which inequality measurement to apply, and (3) on which unit of analysis to focus. The data often dictate the inequality measure that is feasible given the

information available. It is important to understand the advantages and disadvantages of data sources in judging the reliability of inequality measures. The most commonly used data for studying income inequality stem from the annual March *Current Population Survey* (CPS) of households and IRS tax records. Tax records offer some advantages to survey data. Tax records sample wealthier Americans more accurately whereas survey data tend to undersample them; participation in filing a tax return is not voluntary, and the potential costs of providing false information are much higher. At the same time, however, administrative tax data only include households that pay tax and thus ignore the poorest households and the unemployed.[2] While neither tax nor survey data exhaustively capture the true welfare position of individuals,[3] tax data typically lack information on the household context and thus ignore the effects from expenditure differences as well as resource pooling within the family unit. A high-earnings-potential individual such as a doctor or economist in training will appear on tax records as poor, although both can expect high lifetime earnings. Likewise, wealthy households can appear in tax records below the poverty line in years where they do not work or sell assets. Furthermore, administrative tax records often lack important demographic information on the tax unit, rendering it impossible to account for compositional changes to the tax base.

As a result of missing data at the bottom of the income distribution, studies based on tax records tend to choose the 90/50 percentile ratios of income shares to compute inequality. Many previous studies using the CPS data, however, investigate the evolution of inequality in the lower tails of the income distributions, using the 50/10 percentile ratio owing to the issue of top-coding of the highest incomes. Recently, Larrimore et al. (2008) used internal CPS data

[2] Several scholars question the quality of the data used and reliability of the methodology used by Thomas Piketty and others to estimate inequality using administrative tax data (Auten and Splinter 2017; Giles and Giugliano 2014; King 2014; Magness and Murphy 2015; Reynolds 2012; Sutch 2017).
[3] For example, it is difficult to measure in-kind benefits, such as publicly provided goods.

to impute the highest incomes in the public use CPS files that now replace top-coding and allow for more comprehensive measures of inequality that encompass the entire distribution of income. The Gini coefficient serves as the most commonly used comprehensive measure of inequality in the literature and summarizes the share of income accruing to each percentile of the population, from the poorest to the wealthiest.[4] The following analysis therefore uses the Gini coefficient for exposition of inequality trends, with zero indicating absolute equality and one absolute inequality.

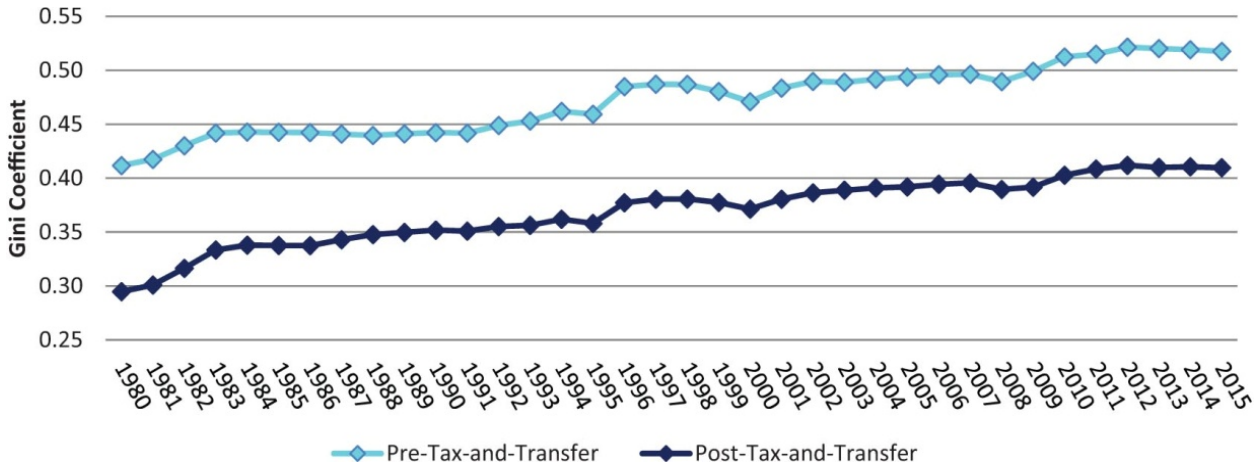
Even among studies using the Gini coefficient to measure inequality, results will vary according to the demographic group investigated and the income concept employed. Taking the entire population of the United States between 1980 and 2016, figure 1 displays the evolution of income inequality implied by the Gini coefficient when measured by percentile at the household level in both pre-tax and post-tax terms. The pre-tax-and-transfer measure is composed of the household sum of pre-tax personal market income or losses during the previous year, including wage and salary income, farm and business income, and income from property, dividends, and pensions, excluding Social Security. We exclude Social Security from the measure of pre-tax-and-transfer market income owing to the redistributive nature of its replacement rates. Thus, the light blue line in figure 1 depicts the evolution of inequality stemming from market income without considering taxes paid on this income or government transfers made to households. To calculate post-tax-and-transfer income, we first employ the National Bureau of Economic Research (NBER) TAXSIM microsimulation model and obtain net federal and state tax liabilities after accounting for major tax credits and deductions according to the income and demographic composition of each household. In this measure, we also include Social Security

[4] Indices of the generalized entropy family (such as the Thiel index) would likewise serve this purpose, but we prefer the Gini coefficient for the purpose of this paper owing to the straightforward nature of its exposition and interpretation.

payments and welfare transfers. Therefore, the navy blue line in figure 1 depicts the evolution of household income inequality after incomes have been taxed and government transfers received. Owing to data limitations, in particular with regard to in-kind benefits and other noncash government programs, not all transfers can be incorporated into this measure. Consequently, this omission likely leads to overestimation of the post-transfer level of inequality. On the other hand, the omission of in-kind forms of labor market compensation for employees, such as healthcare costs, will likely lead to some underestimation of inequality because higher earners on average receive employer contributions to healthcare[5] and pension funds. Likewise, the TAXSIM calculations of tax liabilities perform an approximation of the true tax liability, and while the model offers a very good estimate of these parameters, it should not be viewed as exhaustive. Because it cannot account for all forms of tax deductions and exemptions, the tax liability is likely overstated for high income groups, which would underestimate the true Gini coefficient. As is standard in the literature, we adjust each measure using the OECD equivalency scale, which accounts for the size of the household and economies of scale possible in larger household units.

[5] The importance in particular of healthcare contributions has increased since 1980, but data are available only beginning in 1992 and are thus excluded to ensure comparability of labor market income over time. We further treat this income factor below.

Figure 1. US Household Income Inequality, 1980–2015



Source: Author's calculations, weighted and adjusted for inflation, from US Census Bureau, *Annual Social and Economic Supplement (ASEC) of the Current Population Survey (CPS)*, 1980–2016 [hereafter March *CPS Supplement*].

Three aspects of the Gini trend lines juxtaposed in figure 1 merit mention. First, the level of post-tax-and-transfer inequality remains approximately 11 percentage points below the pre-tax-and-transfer level of inequality throughout the entire time period investigated, indicating that if we ignore behavioral effects[6] of the tax-and-transfer system, redistribution mechanisms in the tax-benefit system have substantially decreased the level of inequality that would prevail according to earned market income levels. However, it remains unclear to what extent government intervention through taxation and redistribution has fundamentally altered behavior regarding labor supply and household savings, therefore changing pre-tax household wealth. As such, it would be inaccurate to claim that redistribution policies have reduced inequality. A second observation resulting from this exercise is that, despite this measurable redistribution, household income inequality has risen 11 percentage points since 1980. Finally,

[6] Note that we do not attempt a true counterfactual analysis here and acknowledge that changes in government policy with regard to tax-and-transfer levels would inevitably spur behavioral effects in economic activity, effectively changing both pre- and postintervention income.

the trend lines are nonmonotonic, increasing and decreasing with the business cycle. These fluctuations reflect the 1980–1982 recession, the dot-com recession of 2000–2002, and the Great Recession of 2007–2008, in which wealth and therefore the flows of capital income decreased.

The restrictions required in completing this exercise in inequality measurement exemplify many of the limitations imposed by data availability or the lack of knowledge about counterfactual behavioral responses to incentives that are present in existing studies of inequality. Consequently, it proves essential to discuss not only the factors that are measurable, but also the omitted variables and how those omissions will bias results or alter policy recommendations. Furthermore, this attempt to quantify household income inequality before and after policy intervention demonstrates how the aggregate measure of household income inequality, here represented by the Gini coefficient, masks many underlying trends that must be further investigated to understand the drivers of changes in inequality.

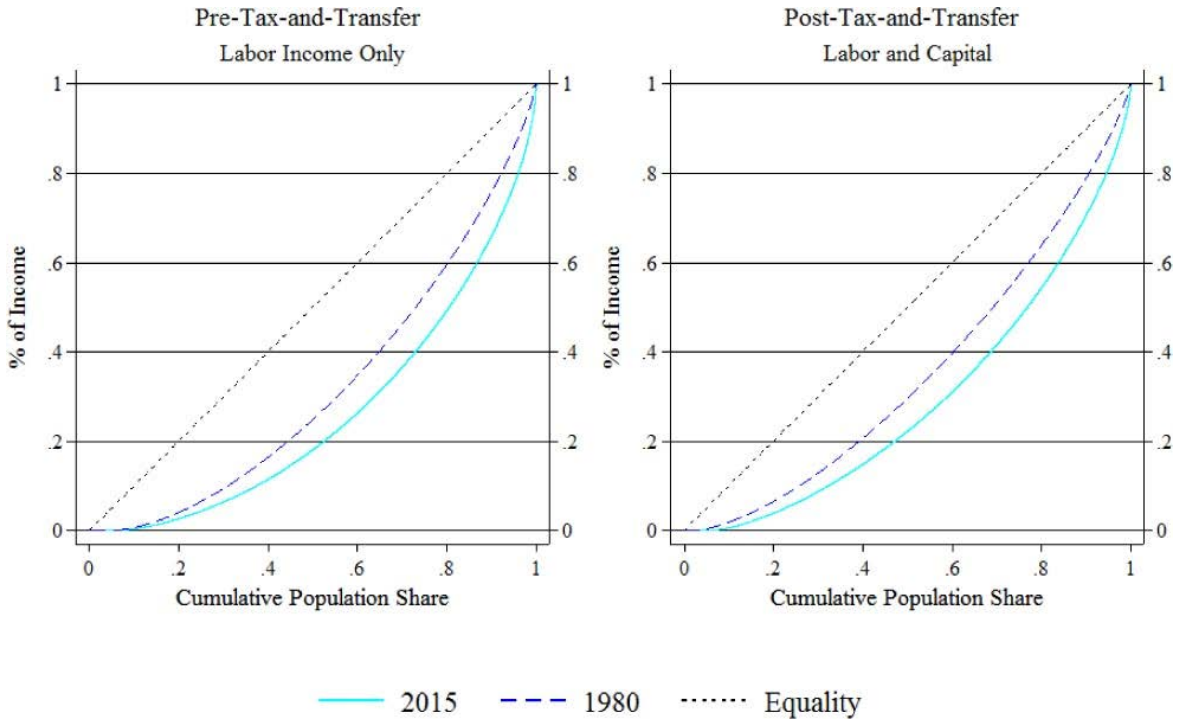
In a first step, we investigate the contribution of labor market income to inequality evaluated at the household level and finally at the individual level. To do so, we restrict the age group of analysis to prime-age workers, exclude households that receive pensions, and focus on current earnings from wages and salary, personal business, and farm income for the pre-tax labor income measure shown in the left panel of figure 2. Doing so limits the effect of the changing age structure of the labor force and the influence of pensions and Social Security income. Figure 2 offers a juxtaposition of household inequality before and after tax-and-benefit intervention (similar to figure 1) but focuses on the changes between the first and last year of observation,

from 1980 to 2015.[7] In addition to net labor earnings (gross earnings less federal and state taxes) and government transfers, the right panel of figure 2 also necessarily includes income from and taxes on dividends and property, as the TAXSIM calculator includes these values for the tax simulation at the household unit. It is therefore not possible to obtain a measure of labor taxes separate from capital taxes using this publicly available simulation model.

The Lorenz curve graphically displays the percentage of the nationally aggregated income (y-axis below) that accrues to each additional percentage of households (x-axis below) when they are ordered from poorest to wealthiest. The black 45-degree line in figure 2 represents a situation in which total equality exists, and for each additional percentage of households, households in that given percentile own an additional percentage of the national income—i.e., 10 percent of the households would claim 10 percent of national income, 50 percent would claim 50 percent of national income, and so on. When the Lorenz curve is closer to the line of equality, the Gini coefficient is small, thus signifying less income inequality.

[7] The Gini coefficient and Lorenz curve are synonymous measures of inequality presented in different ways. The Gini coefficient can be derived from the Lorenz curve; it is the area between the 45-degree line of perfect equality and the Lorenz curve divided by the entire area under the perfect equality line.

Figure 2. Household Labor Income Inequality 1980 vs. 2015 (Lorenz Curves)



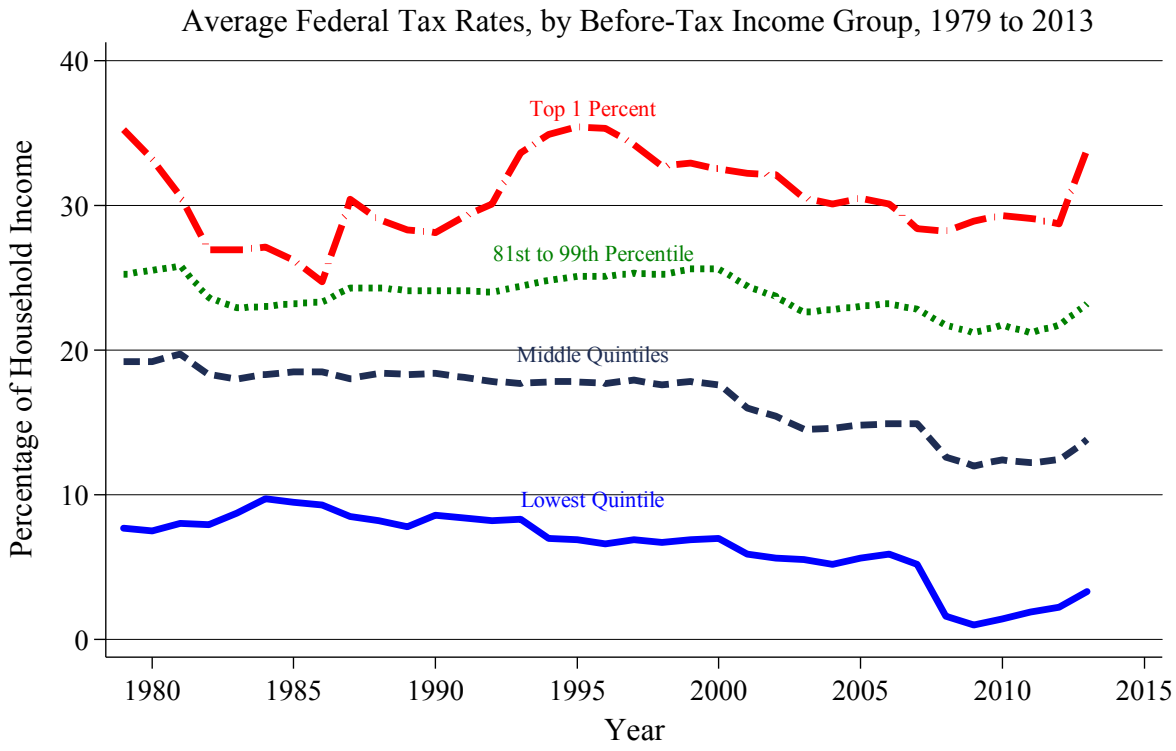
Source: March *CPS Supplement* 1980 and 2015; authors' calculations.

The left panel of figure 2 demonstrates the increase in labor earnings inequality at the household level before taxes and transfers. Many households at the bottom of the distribution in both 1980 and 2015 do not earn any labor income, and therefore a bunching at the bottom of the Lorenz curve ensues. Comparing the lines for the respective years across panels reveals that the decrease in inequality after taxes and transfers tracks the development of pre-tax-and-transfer labor earnings inequality similar to the observation in figure 1, where the pre-tax measure of income included both labor and capital sources. This evidence corroborates the findings of Piketty (2014), who estimates that differences in wage and salary income account for two-thirds of income inequality and are thus the driving component of measurable capital and labor inequality, given current data availability. It is important, however, to note that labor

income is likely better measured than capital income due to payrolls and the limited mobility of labor as opposed to capital.

Moving from the pre-tax-and-transfer to the post-tax-and-transfer measure of inequality, several changes are occurring simultaneously that may affect the distribution in different ways. Both taxes and transfers are intended to equalize household income: progressive taxation taxes higher incomes at increasingly higher marginal rates, and transfers have traditionally been targeted at low-income households. However, the progressivity of tax rates declined in the 1980s, increased in the 1990s, declined again during the 2001–2010 period, and increased again in 2013. As pre-tax income accruing to the top earners has increased, the share of taxes paid by those households has grown at an increasing rate (CBO 2011). As shown in figure 3, the average tax rate paid by the top one percent increased from the mid-1980s to the mid-1990s, decreased from the mid-1990s until 2007, slightly increased during the Great Recession of 2007–2008, and jumped with the retirement of the George W. Bush tax cuts in 2013. Those households in the bottom quintile witnessed a slow and steady decline in average tax rates from the mid-1980s until the Great Recession of 2007–2008. During the Great Recession, the bottom quintile witnessed a steep decline in average tax rates. Since the recession, average tax rates have increased on those in the bottom quintile. All households witnessed an increase in their average tax rates when the Bush tax cuts were not renewed. The expansion of tax credits and deductions over the years has led to nonlinearities in the tax schedule and complicated the measurement of the true tax incidence of households.

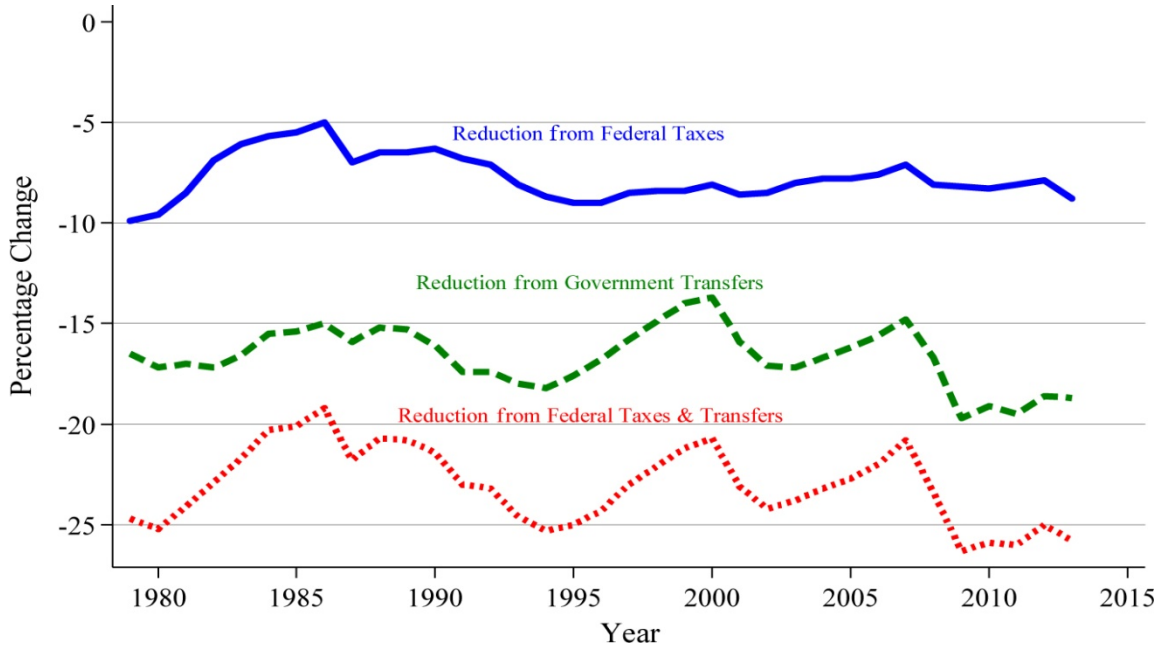
Figure 3. Federal Taxes as a Percentage of Household Income by Income Group, 1979–2013



Source: Congressional Budget Office (CBO), "The Distribution of Household Income and Federal Taxes," 1979–2013.

The decline in the tax rate in the early half of the 1980s is associated with a decrease in the difference between the pre-tax and post-tax inequality measures. As shown in figure 4, this suggests that the initial tax decrease enacted during Ronald Reagan's administration, along with higher interest rates, may have raised post-tax inequality.

Figure 4. Percent Change in Gini Coefficient from Taxes and Transfers



Source: Congressional Budget Office (CBO), "The Distribution of Household Income and Federal Taxes," 1979–2013.

The tax law changes in 1986 and 1988 are associated with a larger difference between pre-tax and post-tax inequality, suggesting that tax rate reductions in the latter half of the 1980s may have served to reduce post-tax inequality. During the 1990s, post-tax-and-transfer inequality increased due to the decline in transfers. The tax increase under Bill Clinton does not appear to alter the relationship between pre-tax and post-tax inequality. The Bush tax cut also appears to have little to no effect on post-tax inequality. In contrast, transfers from 2001 through 2003 do appear to have reduced post-transfer inequality. Likewise, transfers during the Great Recession caused large reductions in post-transfer inequality. But post-tax, post-transfer inequality falls slightly when the Bush era tax-and-transfer policies are retired under Barack Obama's administration in 2013.

With respect to the equalizing effect of government transfers, according to the Congressional Budget Office (CBO 2016), between 1979 and 2013, federal government transfers have expanded from just below 10 percent of market income in 1979 to a high of 16.7 percent in 2009. However, these transfers have become less concentrated in the bottom of the income distribution over the past 35 years.

Because most households file joint tax returns and benefits depend on household composition, it proves difficult to identify the change in pre- and post-tax-and-benefit labor earnings inequality at the individual level. Therefore, in sections 3 and 4, we attempt to disentangle the drivers of pre-tax-and-transfer wage rates of individuals in order to better understand the contribution of gross hourly wages (individual labor prices) to growing inequality at the household level.

Section 2. The Role of Marital Sorting and Changes to Household Composition

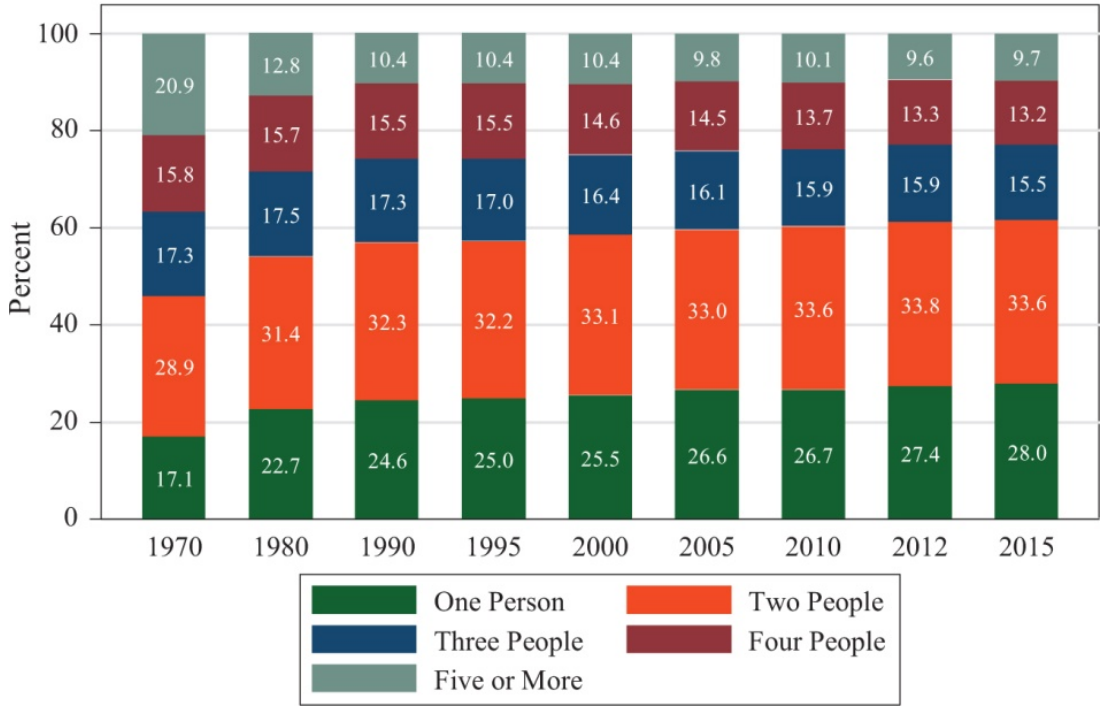
In this section, we further explore the role of household composition and assortative mating for total income. Absent any changes in wages, taxes, or transfers over time, income inequality across households can also be affected through changes in household composition. A process known as "assortative mating" has led to more homogenous households over time: high-income earners tended to marry other high-income earners more often in 2015 than was the case in 1980.[8] Moreover, the overall size of households has decreased over time, which could have either a positive or negative effect on inequality. Households may serve as a way to reduce individual inequality by enabling family members to pool resources, such as a parent for a child. Equivalency scales capture the effect of such economies of scale within a

[8] See Greenwood et al. (2014) for an analysis of the impact of marital sorting on income inequality in the United States using Census data from 1960 through 2005. Further papers include Cancian and Reed (2012) and Schwartz (2010).

household. Depending on which factor dominates, changes to household composition could increase or decrease inequality of total household income.

According to the US Census Bureau, household size in the United States has decreased drastically over the past 40 years. As shown in figure 5, only 17.1 percent of households consisted of one person in 1970, while 20.9 percent of households consisted of five or more members. By 1990, these large families of five or more had declined to only 10.4 percent of households, while single-headed households had increased to 24.6 percent—an increase of 7.5 percentage points. By 2015, 28 percent of households consisted of a single adult, while only 9.7 percent had five or more household members. Overall average household size decreased from 3.1 individuals to 2.5 individuals between 1970 and 2015.

Figure 5. Household by Size in the United States, 1970–2015



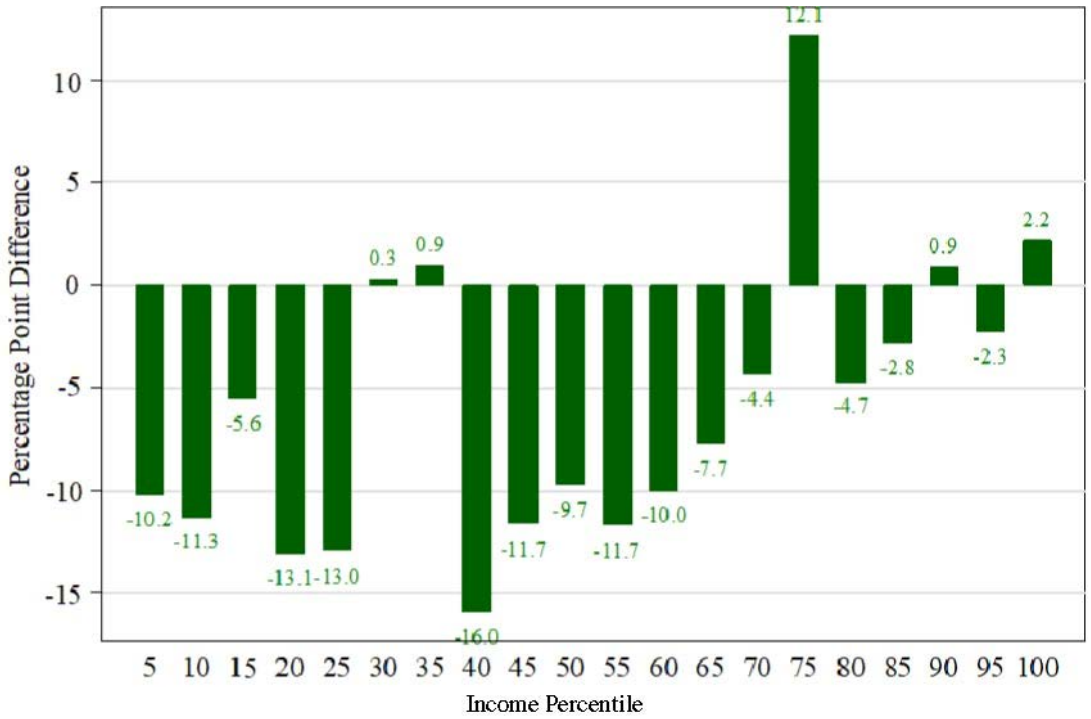
Source: US Census Bureau, Current Population Survey, March and Annual Social and Economic Supplements, "HH-4. Housholds by Size: 1960 to Present," November 15, 2017, available for download at https://www2.census.gov/programs-surveys/demo/tables/families/time-series/households/hh4.xls.

Beyond size, household types have changed over time. In 1970, 70.6 percent of households consisted of married couples with or without children. Singles living alone consisted of 17.1 percent of households, and other families, including single parents, represented 10.6 percent of households. By 1990, other family types, including single parents, represented 14.8 percent of households—a 4.2 percentage point increase from 1970. Single-headed households in 1990 represented 25.6 percent of all households, or an 8.5 percentage point increase. Almost all increases were driven by the decline in married couples with children. Between 1970 and 1990, married couples declined to 56.1 percent, a drop of 14.5 percentage points. By the year 2000, married couples represented only 52.8 percent of all households, and by 2010 only 49.7 percent. This steep decline in the number of households with two adults and the increase in the fraction headed by one, especially during the 1980s, suggests that more than one-fifth of the increase in household inequality may have come from bifurcation in household composition (Karoly and Burtless 1995; Burtless 1999; Daly and Valletta 2006). For instance, Larrimore (2014) estimates that declining marriage rates explain 23 percent of the increase in household income Gini coefficients between 1979 and 2007.

This decline in marriage rates, however, has not progressed uniformly across the income distribution. Marriage rates have declined much less for top-earning men as compared with men at the lower end of the wage distribution. According to the Hamilton Project, men whose earnings place them at the 20th percentile witnessed a 35-percentage-point reduction in marriage rates from 1970 to 2011, while men at the 50th percentile saw a 28-percentage-point reduction (Greenstone and Looney 2012). For men at the 90th percentile, this decline consisted of only 12.5 percentage points (Greenstone and Looney 2012).

We find larger differences in marriage rates across female wage earners. As shown in figure 6, women whose earnings place them at or below the 70th percentile have mostly witnessed a decline in marriage rates. However, women in two of the top three ventiles (increments of five percentiles) have experienced an increase in marriage rates. The top 5 percent of female earners witnessed the second-largest increase of 2.2 percentage points. Because female top earners are much more likely to marry in 2016 than in 1980, assortative mating increases measured household inequality.

Figure 6. Change in Share Married by Women's Income, 1980 vs. 2016

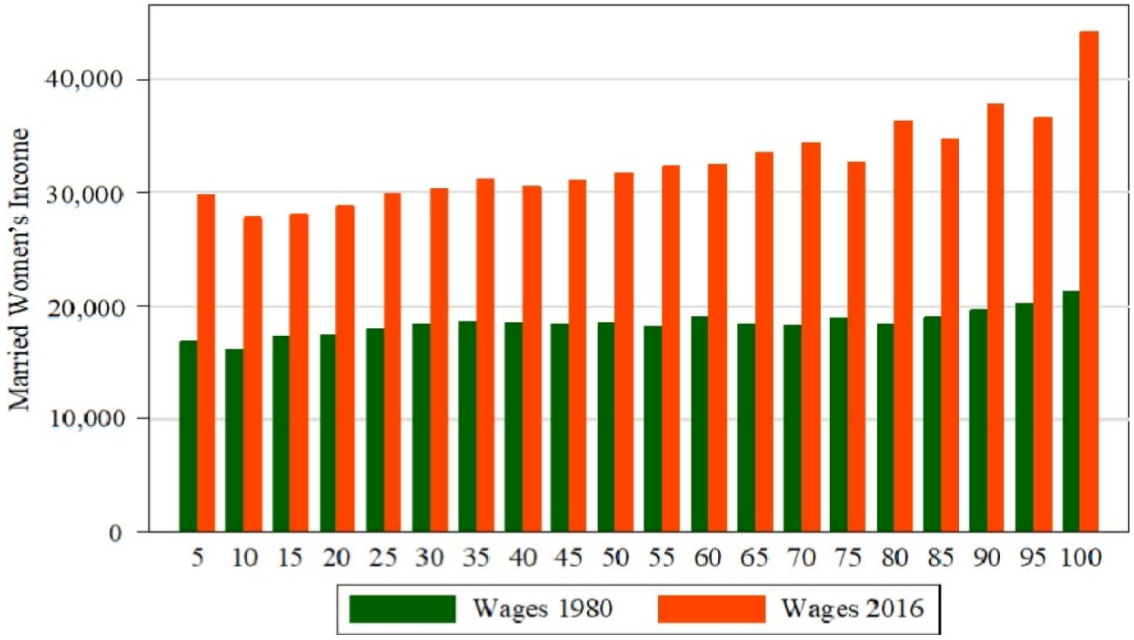


Source: March *CPS Supplement*, 1980 and 2016, authors' own calculations (in 1999 USD).

Not only are top-earning men and women more likely to marry than lower-earning men and women, but top-earning men and women are more likely to marry each other than to marry

people farther down the income distribution. Figure 7 shows that the level of working wives' earnings is positively correlated with their husbands' earnings. In 1980, married men whose earnings placed them in the 10th ventile were married to women who earned about $23,300 a year (in 1999 US dollars, or USD), while men in the top ventile were married to women who earned about $28,900 per year, for a difference of approximately $5,600. By 2016, this difference had increased to approximately $13,800 (in 1999 USD).

Figure 7. Married Women's Income by Husbands' Earnings Ventile, 1980 vs. 2016



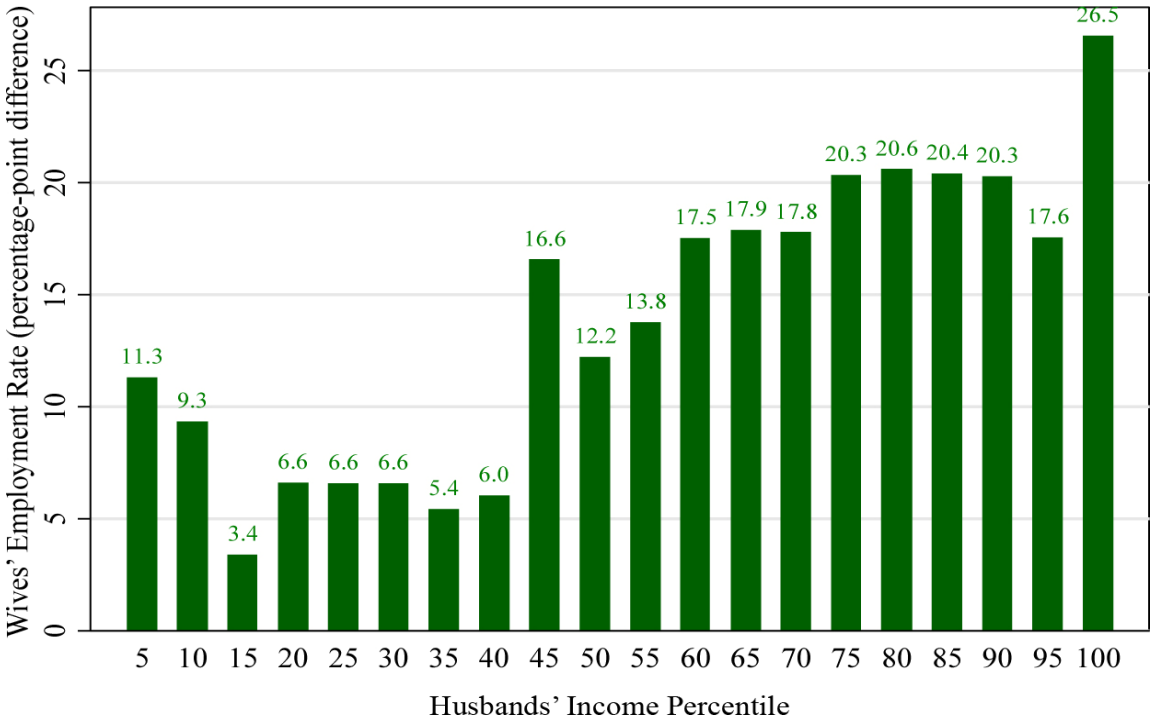
Source: March *CPS Supplement* 1980 and 2016, authors' own calculations (in 1999 USD).

The increase in assortative mating in the United States has been examined by many scholars (Hou and Myles 2008; Lam 1997; Qian and Preston 1993; Schwartz and Mare 2005). Lam (1997), Schwartz (2010), and Greenwood et. al. (2014) investigate the relationship between assortative mating and income inequality. Greenwood et al. (2014) reveal that "if people

matched in 2005 according to the 1960 standardized mating pattern there would be a significant reduction in income inequality; i.e., the Gini drops from 0.43 to 0.35" (Greenwood et al. 2014, 3).

Not only are earnings of spouses correlated, but the likelihood that a spouse of a top male earner is employed has increased over time for most, but not all, OECD countries. Figure 8 shows that this phenomenon is present in the United States. For male earners in the top 5 percent, the employment rate of their spouses has increased by 26.5 percentage points between 1980 and 2016, the largest increase for any ventile. The employment rate of wives with husbands in the top 40 percent has jumped 17 percentage points or more. For husbands in the bottom quarter, the largest increase is 11.3 percentage points for husbands in the bottom 5 percent.

Figure 8. Difference in Wives' Employment Rates by Husbands' Income, 1980 vs. 2016



Source: March *CPS Supplement* 1980 and 2016, authors' own calculations.

Overall, this increasing correlation between the earnings of husband and wife appears to be contributing to the increase in household inequality (Cancian, Danziger, and Gottschalk 1994; Blackburn and Bloom 1995; Cancian and Reed 1998, 1999; Hyslop 2001; Schwartz 2010). Given the income disparities between workers and nonworkers, this last phenomenon further exacerbates inequality trends when the level of analysis is elevated to the household level.

Section 3. Individual Wage and Salary Income

Greenwood et al. (2014) analyze the increase in the Gini coefficient in the United States and find changes in wages across individuals to be the main driver in inequality growth since 1960. In the 1960s, the weekly earnings of male and female college graduates were slightly higher than those of high school graduates. In the 1970s, this earnings gap disappeared, but starting in the 1980s, the earnings gap between college graduates and high school graduates expanded sharply. In addition, those with some college (male), high school graduates (both), and high school dropouts (both) realized a decline in their real weekly wages. Much of this appears to be driven by the increasing returns to skill (Katz and Murphy 1992; Autor, Katz, and Krueger 1998; Autor, Katz, and Kearney 2008).

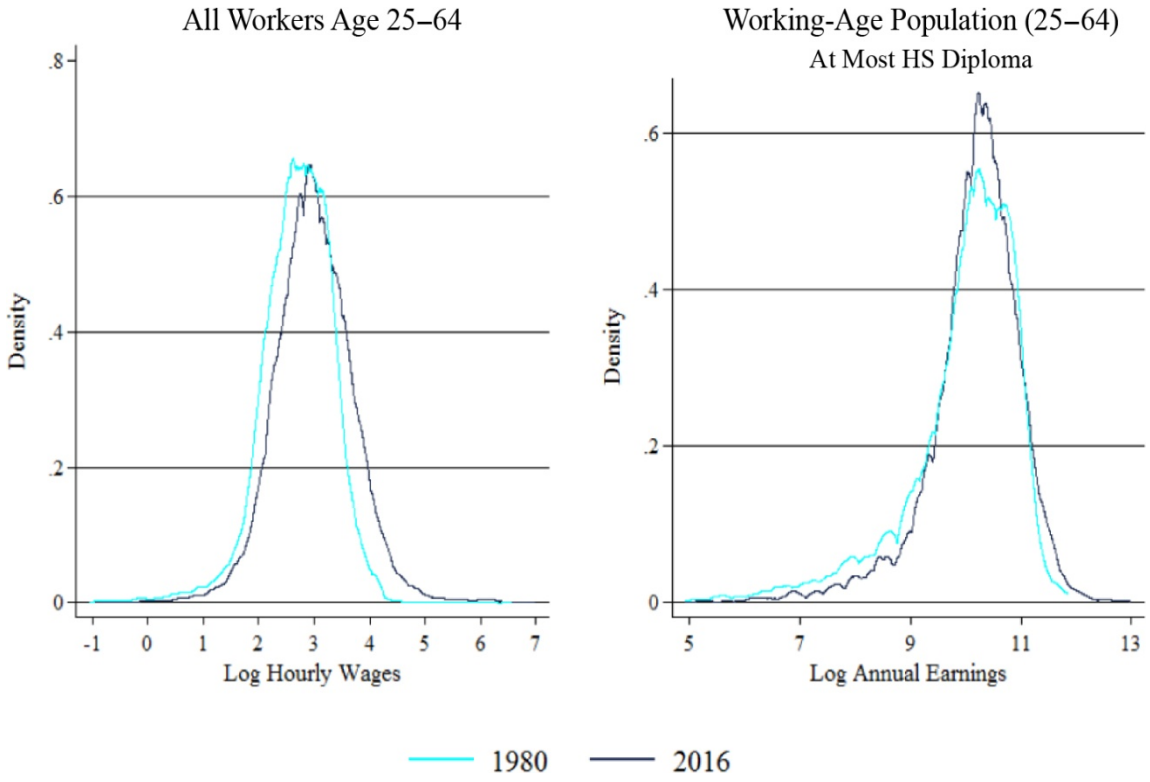
Two related labor market trends work in the same direction to increase the contribution of wage and salary income to inequality: highly educated workers enjoy both higher wage rates and higher employment probabilities compared to their low-skilled and medium-skilled counterparts. For this reason, figure 9 depicts the evolution of the wage distribution for two groups separately: all workers age 25–64 and the working-age population with at most a high school diploma. For reasons of comparability over time, we exclude those younger than 25 from this descriptive analysis owing to the increases in schooling for youths in this age range. While the left panel of figure 9 depicts the distribution of logged wage rates for all workers in this age range, the right

panel restricts the sample to individuals with at most a high school diploma and shows logged annual earnings rather than wage rates in order to capture the impact of changes on the intensive (hours and weeks worked last year) labor supply margin. In other words, the annual earnings measure incorporates effects from marginally employed, underemployed, and seasonal workers with few hours of work, while the log hourly wages of workers exclusively highlight changes in the rate of compensation per hour. Annual earnings include all gross wage and salary income earned during the previous year, and hourly wages are calculated by dividing this sum by the number of weeks and usual weekly hours worked.[9] Both measures include part- and full-time workers, but neither includes potential workers with zero hours.[10]

[9] We plot wages in logarithmic form rather than directly plotting the raw wage data, as this transformation makes the distribution smoother and thus easier to view in its entirety without distortion from outliers.

[10] We exclude this margin in the depiction in order to emphasize changes in worker compensation. This exclusion affects 17 percent of individuals age 25–64 in 1980 and 14 percent of this age group in 2016 who had zero labor market earnings during the previous year.

Figure 9. Wage Distributions among Workers (Logarithmic), 1980 vs. 2016



Source: March *CPS Supplement* 1980 and 2016, and authors' own calculations. Wages have been adjusted to 2016 constant dollars using the Consumer Price Index (CPI) 2016.

Both in terms of hourly wage rates for all workers and annual earnings among the low-skilled (defined as workers having at most a high school diploma), the entire income distribution in 2016 has shifted to the right of what it was in 1980. This shift indicates that, even taking marginal employment of low-skilled workers into account, individuals are earning more in real terms in 2016 than was the case in 1980, and that is true at all earnings percentiles, not only at the top. Therefore, the increase in labor income inequality at the individual level has not occurred at the expense of earnings at the bottom of the distribution in absolute terms. Furthermore, this observation suggests that the driving force behind individual labor earnings inequality stems from relatively larger increases at the top of the income distribution. For example, the median hourly wage in 1980 (in 2016 constant dollars) was $15.29 and the mean

was $18.08. By 2016, the median had risen to $20.00 and the mean to $31.93. Because the average wage of all workers (mean) rose by $13.85, or 77 percent, in real terms during this time period, but the earnings of the average (median) worker only rose by $4.71, or 31 percent, the data demonstrate that compensation rates for high earners grew faster than for the average earner. The median wages in 1980 and 2016 correspond to 2.73 and 3.00 log dollars, respectively, indicated by the peaks in the left panel of figure 8. In the following analysis, we take a more profound look into the dynamics at play for low-wage and high-wage workers throughout the wage distribution.

Section 4. The Effect of Compositional Changes on Individual Wage Inequality in the US Labor Force

To illustrate the effect of changes in the working population on the wage distribution in the United States, we perform a decomposition exercise. Decomposition methods present a standard approach in economics to understanding the separate effects of population characteristics and the so-called returns to these characteristics on changes in the overall wage distribution. For example, the level of education in the workforce has increased in the past two decades, as have the returns to skills, and the latter have been asymmetrical, with growth in labor earnings at higher skill levels surpassing those of low-skilled workers. Decomposing these two forces entails creating a counterfactual situation for the US workforce, holding important characteristics, such as education, constant and then assessing how the wage distribution would change had population characteristics remained unchanged. As such, decompositions offer a quantification of the role of each possible explanatory factor in the wage equation, but they do not attempt to uncover deep structural parameters in a causal, general equilibrium sense. Nevertheless, the decompositions present a powerful tool for

identifying the most substantial driving factors that can then be further analyzed in a causal framework (Fortin, Lemieux, and Firpo 2011).

Since the seminal papers of Oaxaca (1973) and Blinder (1973), which decomposed the effects of changes in stocks and returns to characteristics of the working population at the mean of the distribution, many different decomposition methods have emerged. In the following, we employ Blaise Melly's method of decomposition because it uses quantile regression methods, allowing us to go beyond an analysis of the impact of certain variables on the average wage and explore the heterogeneous effects of these variables on different parts of the wage distribution (Machado and Mata 2005; Melly 2006). Research in several different countries including the United States has shown that education improves wages for people at higher quantiles of the wage distribution more than for those at the bottom of the distribution. Scholars have attributed this observation to the fact that wages have a greater spread at higher income levels (see, for example, Buchinsky 1994; Fitzenberger and Kurz 2003). Table 1 below describes the composition of the US workforce in 1980 and 2016 with respect to employment and key factors known to explain wage differences.

Table 1. Labor Force Composition, 1980 vs. 2016

	1980		2016	
	Prime-age	**Employed**	**Prime-age**	**Employed**
Population size (weighted)	83,234,318	61,678,900	126,333,521	97,258,550
Hourly wage (mean)	14.91	18.30	23.56	28.13
Hourly wage (median)	12.96	15.85	16.35	19.23
Weekly hours worked	32.85	40.27	33.02	40.12
Weekly earnings (mean)	602.72	751.15	900.24	1107.99
Weekly earnings (median)	513.42	648.00	645.83	788.46
Female (%)	51.22	42.08	50.62	46.70
Age (mean)	37.84	37.75	39.36	39.39
Educational attainment (%)				
Less than HS diploma	21.30	17.75	9.47	7.97
HS diploma	40.54	39.82	25.78	24.68
Some college	17.66	18.74	27.79	27.88
College	11.74	13.05	23.55	24.69
Professional/doctoral degree	8.77	10.64	13.42	14.76

Source: March *CPS Supplement*, authors' own calculations. Values are weighted using CPS sample weights unless specified otherwise and wages adjusted for inflation (CPI values stated in 2016 constant dollars). Prime-age refers to individuals age 25–54, and the sample includes those who are in the labor force or able to work. The CPS data is ambiguous before 1992 regarding whether an individual obtained a high school degree or completed 12th grade without a high school diploma. For 1980, we define a high school (HS) degree as having finished the 12th grade. Some college is defined as having attended college without completing a degree or having obtained an associate's degree. College is defined as having obtained a bachelor's degree.

In table 1, two populations are juxtaposed in 1980 and 2016: (1) the prime working-age population (25–54) of those either working or able to work and (2) a subpopulation of the former, including only workers. As is common in the literature, we restrict the age group to 25–54 years in order to avoid including full-time students as well as those in (early) retirement. Rather than comparing the labor force (employed and unemployed) with those employed, we compare the entire prime-age population to the sample of employed individuals in order to account for discouraged workers who have left the labor force and stopped searching for a job but who are able to work. The size and significance of this group has increased over time.

Furthermore, table 1 demonstrates that in 2016, the prime working-age population was on average more educated than in 1980, and employment trends have developed asymmetrically by educational attainment. Consequently, increases in education could be driving a large portion of wage inequality in the United States. We investigate this relationship further in the results below.

Moving from the description of the US labor force with respect to central characteristics that influence wage rates to the returns to these characteristics, we estimate 10 quantile regressions (by individual gross wage decile) of the log hourly wage on age, a quadratic in age, years of education, a dummy for being male, and a dummy for being married. Age is defined as a continuous variable whereas education is a categorical variable comprised of the five possible attainment categories from table 1: less than a high school diploma, high school diploma, some college, bachelor's degree, and advanced degree (master's, professional, or doctoral). The sample consists of prime-age workers. Regressions are run separately for 1980 and 2016, and the coefficient results for each of these 10 equations for each year are plotted in figure 10, accompanied by a 95 percent confidence interval for statistical significance. The left column thus represents the "prices" or returns to each of the dependent variables for 1980, and the middle column shows the estimated returns in 2016. Finally, the right column tests the statistical significance of the differences in returns to each of the explanatory variables between the two years.

The first row in figure 10 displays the age premium. In 1980, an increase in one year of age corresponded on average to a 3.5 percent increase in wages across all wage deciles. By 2016, the age premium increased slightly in the lowest deciles to roughly 4.5 percent, with a larger increase for higher earners such that in 2016 an additional year of age corresponded to almost a 6

percent increase in hourly wages. The changes between the two years, seen in the upper right-hand corner of figure 10, reveal that the age premium, which is correlated with experience, has contributed to inequality in the past 36 years because it increased wages more for higher compensation rates than for the lower wage groups.

The second row of figure 10 presents results for what can be deemed the gender wage gap. Because the gender variable takes the value of unity when the individual is male, the positive coefficients indicate that the hourly price of male labor is on average higher than that for females. In 1980, the gender wage gap was very high, with the median male worker earning an hourly rate that was roughly 50 percent higher than that of the average female worker. Interestingly, the gap was highest for earners in the middle of the wage distribution rather than at the highest wage rates: both for the lowest wage earners and for the highest wage earners, this gap was around 44 percent. By 2016, the gender wage gap had been nearly cut in half for the median earner, and the shape of the wage gap across deciles had fundamentally changed. In 2016, the gap increases from the lowest (roughly 24 percent) to the highest (28 percent) deciles, increasing with the wage rate, albeit very slightly decreasing in the highest wage decile. As women earn less than men on average, the spread of wages for women is smaller, and thus the growth of female employment has lessened overall wage inequality in the labor force. Because exhaustively explaining the gender pay gap would go beyond the scope of this exercise, our regression does not include controls for industry or occupation, both of which have been found in the literature to somewhat reduce the estimated gender pay gap (Blau and Kahn 2016).

The third row of figure 10 displays the marriage premium for wages. Consistently positive coefficients indicate that married workers earn more than nonmarried workers, and being married corresponds to a higher premium in 2016 than was the case in 1980. All else

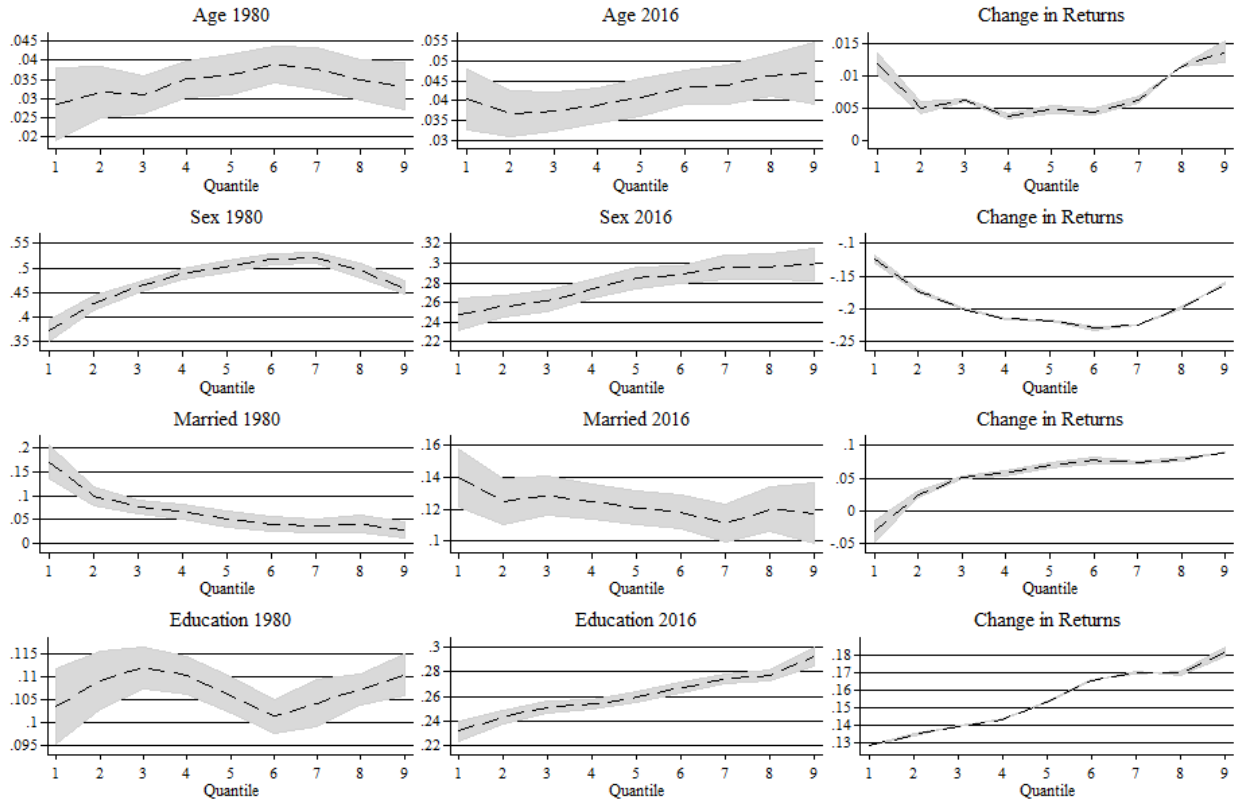
equal, married individuals in 1980 earned 12 percent more in the lowest wage decile than their unmarried counterparts, whereas this difference was less than 5 percent in the highest wage decile. In 2016, the average wage difference between the two groups remained roughly unchanged in the lowest earner decile but increased in the higher wage earner groups. Therefore, the contribution of these changes in the marriage premium over time has been to increase wage inequality. As with the other variables in the regression, this association should not be interpreted as causal but simply as a correlation. A vast literature suggests causal effects in both directions: high earners may be more attractive on the marriage market and therefore more likely to be married, while at the same time marriage may make men in particular more productive, which then increases wage rates.[11] Furthermore, when the marriage premium is aggregated to the household level, its contribution to inequality increases even more. Evidence suggests that assortative mating has increased in the most recent decades in the United States, with high earners more likely to marry other high earners, leading to more homogeneous households.

Quantitatively, the most significant driver of wage inequality among the factors investigated pertains to the increase in returns to education, exhibited in the bottom row of figure 10. The return to education has increased significantly in the past 36 years and much more so in the upper quantiles than the lower quantiles of the wage distribution. In 1980, the education premium amounted to 13.5 percent on average in the lowest and 13.75 percent in the highest wage decile, meaning that for an additional level of educational attainment, a worker could expect a 13.5 percent increase in hourly wage. For the average worker, that premium has now almost doubled in 2016 and amounts to 26 percent at the median. More important, however, for inequality dynamics, the effect across the wage distribution in 2016 is increasing with income, whereas in 1980 the effect of education did not differ much by wage decile. In other words, a

[11] Leonard and Stanley (2015) offer an overview in the form of a meta-analysis.

higher level of educational attainment does not only result in a higher wage, but higher earners profit more from education than do low-wage earners. Consequently, increasing returns to education—generally viewed as a positive economic development—have significantly contributed to an expansion in wage inequality.

Figure 10. Regression Coefficients by Wage Quantile, 1980–2016



Note: For the standard errors of the changes in returns, we bootstrap with 500 iterations and make the simplifying assumption that the distributions in 1980 and 2016 are weakly independent.

Source: March *CPS Supplement* 1980 to 2016.

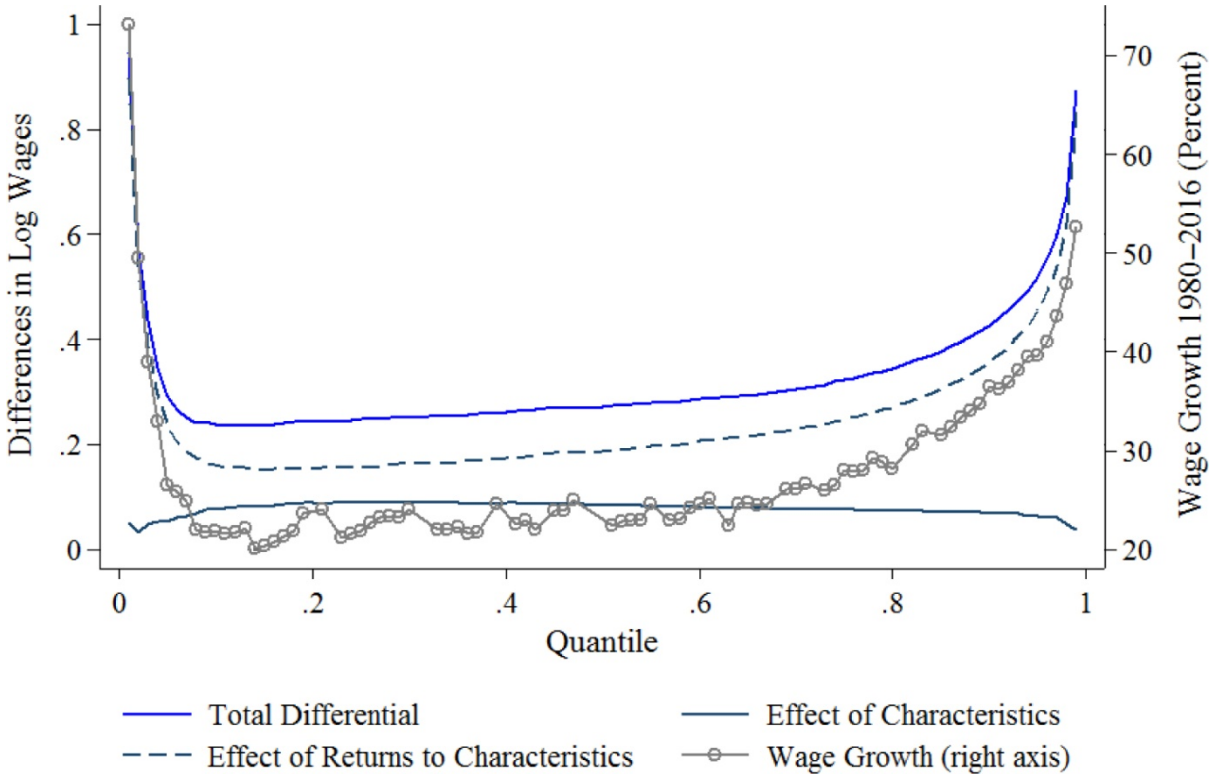
In particular, the results with respect to the role of education in increasing inequality are in line with Autor, Levy, and Murnane (2003) and Autor, Katz, and Kearney (2008), who explain this

observed polarization in skill-biased wages as a change in firm demand for certain occupations and competencies. Occupations that are routine in nature and are easy to replicate through technological innovation have witnessed a decline in their wages because lower-cost technology can now substitute for these routine occupations. Occupations that are either physically unique, creative, or otherwise not routine were not easily substitutable and, more important, were able to increase in their productivity through technology. The increase in productivity resulted in higher wages. Therefore, some occupations realized higher wages through technology while others witnessed declining wages.

Finally, the last part of this exercise involves decomposing the overall changes in wage inequality into the effects of changes in the composition of the US labor force from table 1 and the effects of returns to these characteristics from figure 10. Using Blaise Melly's statistical package rqdeco, we first estimate the distribution of logged hourly wages conditional on the observed characteristics of age, education, sex, and marital status with the same linear quantile regressions, as in the above exercise, but estimated by wage percentiles rather than deciles for increased accuracy. Additionally, the decomposition adds a second step that integrates the conditional distribution of logged hourly wages over these independent variables in order to obtain the estimated unconditional distribution of log hourly wages. Taking the characteristics of the labor force from 2016 and applying them to the coefficients estimated with the quantile regressions from 1980, it is then possible to estimate the counterfactual distribution of hourly wages if the labor force characteristics of 2016 were remunerated as they were in 1980. Likewise, it is possible to obtain the counterfactual distribution of wages using characteristics from 1980 and prices from 2016. As a result, we obtain counterfactual distributions that can be

separated into the effects of changing coefficients and the effects of changing characteristics on wage inequality.[12] Figure 11 graphs these contributions.

Figure 11. Decomposition Wage Differences in 1980 and 2016: Characteristics vs. Prices



Source: March *CPS Supplement* 1980 and 2016, authors' own calculations. Adjusted to 2016 CPI dollars.

Figure 11 graphs the difference in the wage distribution in 2016 compared with 1980. The total differential captures the composite change in the distribution driven by changes in the workforce composition with regard to age, sex, marital status, and education as well as by the returns to these attributes, as depicted in figure 10. This total differential and its two components, characteristics of the labor force and returns to those characteristics, are shown on the left-side vertical axis. For ease of interpretation, the right-side vertical axis additionally

[12] For more details about this estimator, see Melly (2006).

translates the total differential into a growth rate in real hourly wage changes from 1980 to 2016. The largest changes can be observed in the extreme tails of the wage distribution, also reflected in figure 9. According to the total differential, wages between 1980 and 2016 increased dramatically by approximately 50–73 percent (right axis) in the very lowest percentiles of the wage distribution, between 21 and 25 percent in the middle of the wage distribution with little difference in growth rates between the 10th and 6th decile, and beginning in the upper 7th decile, growth rates in log hourly wages increased more rapidly, from 26 to 52 percent.

Remarkably, the line capturing the contribution of changes in characteristics to the total wage differential closely tracks the movement in wage changes overall, indicating that changes in prices, or returns to education, age, marital status, and gender rather than changes to the composition of these attributes in the workforce, are the main factor explaining differential wage growth throughout the distribution. The role of prices is most dominant in the lowest and highest tails of the wage distribution. In the lowest 5th percentile of wages, changes in the returns to characteristics explain between 82 and 95 percent of real hourly wage changes between the years 1980 and 2016. In the upper 10th percentile of wages, changes in returns to characteristics explain 84 to 96 percent of the total differential. Between the 10th and 50th percentiles of the hourly wage distribution, returns to characteristics explain between 63 and 67 percent of overall wage changes. Beginning roughly at the median of the distribution, the component of the total differential in wages attributed to changes in returns to characteristics increases steadily. In contrast, changes to the composition of the workforce have had less impact on changes to the wage distribution and have slightly dampened the increase in wage growth in the upper portion of the wage distribution.

In sum, the decomposition exercise has shown that the expansion of female labor force participation has contributed to a reduction in observed wage inequality, while an aging, more experienced, and more educated workforce on average has increased measured wage inequality. Nevertheless, the impact of these changes in worker characteristics on wage growth has been muted by more significant effects of changes in the returns to these attributes. Rather than attempting to uncover deep causal relationships between these characteristics and wages, this exercise demonstrates how dynamics in the labor market are reflected in wage trends throughout the distribution, all else equal. While results help explain wage dynamics in the United States between 1980 and 2016, no unambiguous policy recommendation ensue. The role of educational attainment in determining wages, for instance, is apparent. However, if the supply of educated workers increases, prices (wages) for those workers are likely to decrease. In a similar sense, an increase in the demand for low-skilled labor would increase wages in the lower tail of the distribution.

Section 5. The Role of Nonwage Compensation

A recurring theme in this paper relates to measured and unmeasured income. This section devotes more detail to the dynamics of nonwage and salary compensation, which often elude measurement but have expanded in importance over time. In response to tax law changes in the past few decades, workers and their employers have altered the composition of their compensation. As workers began shifting their compensation away from income and lowering their reported taxable income, the difference between total compensation and total reported income has increased. By lowering the reported income of non-top earners, pre-tax measures miss a growing portion of non-top-earner compensation. Failing to account for this shift in income composition lowers the measured growth in total income and thus exaggerates the

measured share of income at the top, while it underestimates inequality between the lowest deciles of workers who are marginally employed or not employed vis-à-vis better-compensated workers. Two important areas where this has likely taken place involve individual retirement accounts and health insurance.

As noted by Burtless and Milusheva (2013),

> Most labor economists believe that in the long run, much or all of the burden of employer costs for fringe benefits falls on workers (Blumberg 1999; Gruber 2000; Jensen and Morrisey 2001). If employers are largely indifferent about the composition of pay they offer workers, the elements of the compensation package will be determined by legal requirements and workers' preferences. . . . Because workers are free to work for employers that do not provide those benefits, it is widely assumed that the nonmandatory benefits provided to employees must be worth approximately as much to the workers who receive them as the net pay they give up in order to obtain them. Employer-sponsored health and retirement benefits provide a substantial income tax advantage. (Burtless and Milusheva 2013, 87)

Burtless and Milusheva document the growth in nonwage labor compensation since 1950. In 1950, nonwage compensation accounted for just over 5 percent of employee compensation. By 1970, the amount had doubled to 10 percent. During the 1970s, nonwage compensation increased so that by the end of the decade it was up to just below 16 percent. Beyond a decline in the 1990s, nonwage compensation was up to just under 20 percent by 2010. By failing to account for this decline in the share of taxable, monetary wage compensation, the growth in the measured income shares by top earners may be overestimated.

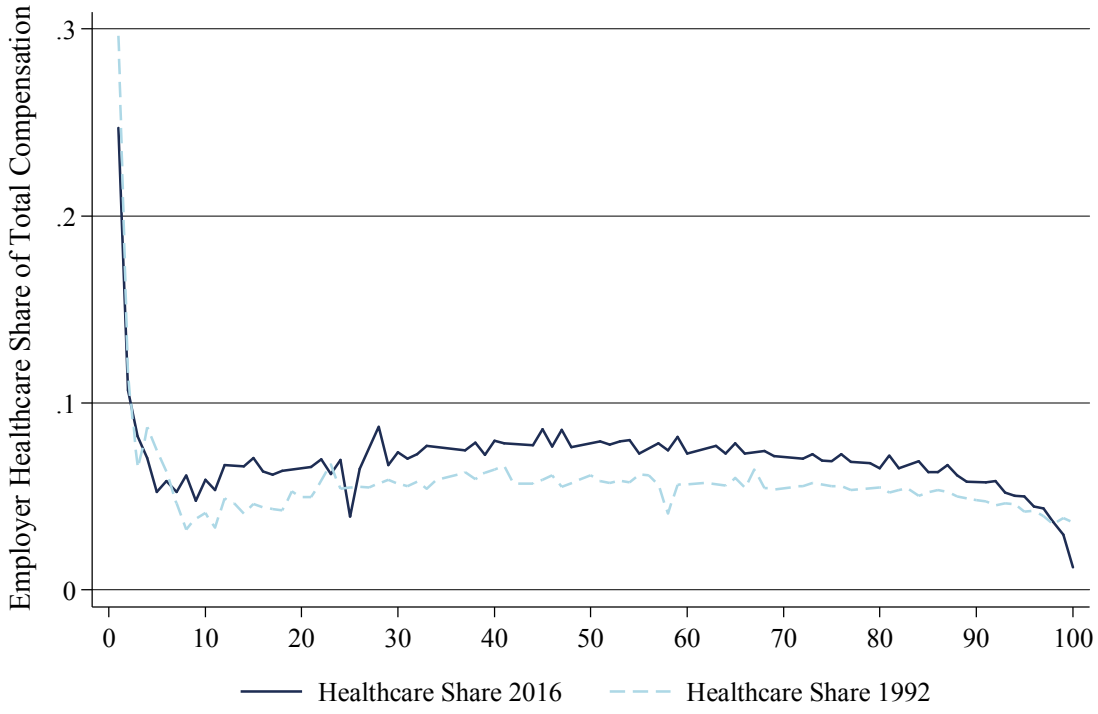
Per Burtless and Milusheva, much of the growth in nonwage and thus nontaxable compensation came in the form of health and retirement insurance. Pierce (2010) demonstrates that retirement benefits also declined as a share of wage income for those in the top one percent. In 1987, higher-income earners received a greater fraction of their compensation in the form of retirement compensation than all other wage earners. From 1987 to 1997, this share declined from just under 6 percent to just over 4 percent. In addition, this decline was larger than the

decline witnessed by other workers in the top 20 percent. Therefore, by 1997, workers at the 80th percentile received a similar fraction of their compensation in the form of retirement benefits. This remained true for workers at the 85th percentile by 2007. Including this retirement share lowered the compensation inequality between top earners and other earners in the top quintile.

Employer-based health insurance provides an even greater example of the importance of nonwage compensation and optimal income shifting during the 1990s and early 2000s. Pierce (2010) calculates that the benefit share of health insurance has changed by income percentile from 1987 to 2007. Over the period from 1987 through 2007, top income earners received a smaller portion of their compensation in the form of health insurance than all but the bottom 20 percent of wage earners. As shown in figure 12, during the 1990s and the first decade of the 21st century, the shift toward health insurance was greater for those between the 20th and 80th percentiles than for those in the top 20 percent.[13] For instance, from 1992 to 2016, the employer health insurance contribution for a worker at the 50th percentile increased from 6.1 percent to 7.6 percent of wages, or an increase of 1.5 percentage points. During the same period, workers at the 95th percentile witnessed a 1.1 percentage point decline, from 6.1 to 5.0 percent. The 99th percentile worker witnessed a decline of 0.9 percentage points. Given that top earners represent only 1 percent of the workforce, this is a substantial increase in the total income shifted away from measured salary and wages used in the income share calculations.

[13] Ideally, we would compare 1980 to 2016. Unfortunately, the Bureau of Labor Statistics (BLS) did not begin collecting this information until 1992.

Figure 12. Employer Healthcare Share by Income Percentiles, 1992 and 2016



Source: March *CPS Supplement* 1992 and 2016, authors' own calculations.

As noted by Pierce (2010), "It seems clear that health insurance premium increases acted to raise measured compensation more for workers in jobs in the broad middle of the wage distribution." Failing to account for the income shifting by earners outside the top one percent exaggerates the measured increase in top income shares relative to others. Using labor and nonlabor income without accounting for nonwage compensation will upwardly bias any measure of income inequality.

Section 6. Capital Income and Wealth Flows

Publicly available data on stocks and shares of wealth across household deciles in the United States and their evolution over time remain scarce. Although we do not investigate wealth

inequality (a stock variable), it is closely related to its corresponding flow variable, capital income. According to Alvaredo et al. (2014), top income earners in the top percentile of the US total gross income distribution received about 50 percent of their income from capital sources such as interest, dividends, and rent in the early part of the 20th century. Capital income sources retained their importance throughout the Great Depression when they comprised from 35 percent to just under 50 percent of gross income. Top earners' share of income from capital sources steeply declined from just under 36 percent to about 20 percent during World War II. Capital income then slowly declined from about 30 percent to just under 20 percent during the 1950s and into the 1960s. This general decline continued throughout the remainder of the 20th century, reaching a minimum of just under 10 percent by 2000. Capital income then began to slowly increase in the first decade of the 21st century, with capital income reaching a maximum of 14 percent in 2007 only to decline during the Great Recession.

In his 2014 book, Thomas Piketty combines several heterogeneous datasets into one long time series dating back to 1913 in order to show evidence for the rise in wealth inequality. In their review of the book, Giles and Giugliano (2014) raise many concerns regarding the computations in the analysis and discover that plotting wealth shares for each of these datasets separately does not show increasing inequality. In the ensuing discussion about the critiques to the accuracy of wealth inequality in the United States, Piketty recognizes that his measurement of wealth in the United States presents a somewhat speculative estimate given the limited data available. Recent research in the field therefore uses the Survey of Consumer Finances (SCF) of the Federal Reserve Board to investigate capital income and wealth inequality (see, for example, Looney and Moore 2016; Saez and Zucman 2016). The SCF provides a triennial survey with the most comprehensive, reliable measure for capital income in the United States between 1989 and

2016, with the most recently available data covering 2013 (see Bricker et al. 2014 for a synopsis of recent trends). For the estimation of capital income, these data present an alternative to the March CPS data for the estimation of capital income, although the latter include richer demographic variables and a longer time series.

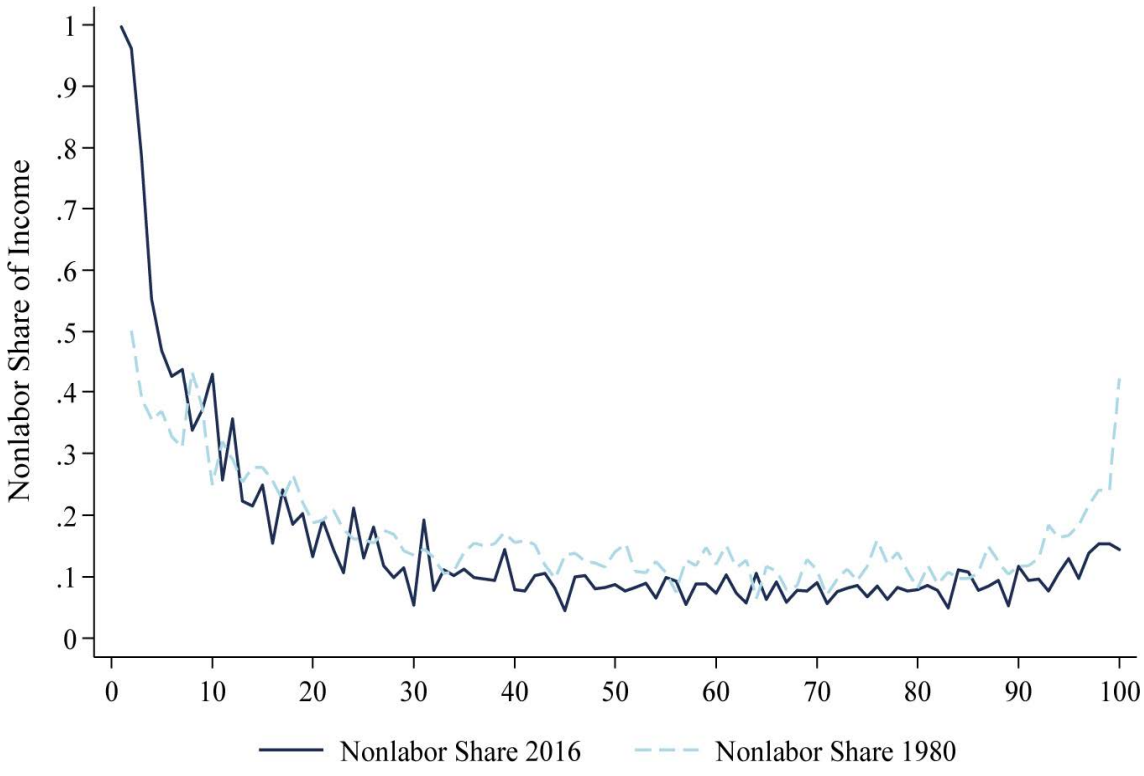
Capital income is only one source of nonwage income. Moreover, capital income and nonwage income can often be negative. One way to estimate nonwage income is by subtracting wage and salary income from total income.[14] Figure 13 reports the nonlabor income for each total income percentile for 1980 and 2016. The nonlabor share of income has decreased for almost all income groups. The share has declined the most for those above the 90th percentile. In other words, although much of the increase in total income inequality in the United States is driven by earners in the top 10 percent, it is not due to the increases in nonlabor, but rather increases in wage labor income.

In this respect, the United States is quite unique. Considering the top 20 percent of households in a broader set of 17 OECD countries over the last 30 years, only three—the United States, Italy, and Chile—have witnessed a decline in the nonlabor income share (a large portion of which is represented by the capital income studied by Piketty and others) for those in the top quintile (OECD 2011). Moreover, the United States reports the largest decline in the share of capital income for households in the top quintile, with the top quintile witnessing a decline that is 3.6 percentage points larger than those in the bottom quintile (OECD 2011). Over the same period, France has witnessed a 6.8 percentage point increase while Sweden has witnessed a 10.1 percentage point increase (OECD 2011). Figure 13 shows the development of the nonlabor share

[14] Total income includes wage and salary income, farm and nonfarm business income, Social Security income, public assistance income, retirement income, supplemental security income (SSI), dividends, rent, trusts, interest, and capital gains and losses. Total income does not include noncash benefits, such as employers' contributions to health insurance.

of total personal income in the United States between 1980 and 2016 by plotting the percentage of nonlabor income (y-axis) that accrues to each total personal income percentile. Nonlabor income includes supplements to wages and salary, proprietors' income, rental income, income on assets, and current transfers less social insurance contributions, and is taken from the March *CPS Supplement* data. Unlike those in most other developed countries, those in the top 10 percent in the United States have witnessed a decline in their share of nonlabor income, especially when compared to workers in the 10th to 40th percentiles.

Figure 13. Nonlabor Share of Income by Percentiles, 1980 and 2016



Source: March *CPS Supplement* 1980 and 2016, authors' own calculations.

Section 7. Tax Response Elasticity

While the literature and estimates cited here do point to rising reported capital income, some of this increase may be attributed to changes in behavior leading to higher reported capital earnings rather than changes in actual wealth. Tax legislation reforms may alter reported income not due to changes in pre-tax compensation, but simply because they create incentives to split the share of income reported on individual versus business tax returns in a way that minimizes the household tax burden. Tax shifting does not alter workers' total compensation but does alter the amount of income reported on their individual tax form. Therefore, measured changes in inequality may result simply from changes in reported income rather than changes in earned income (Sivadasan and Slemrod 2006). These responses become especially relevant when simultaneous changes in various types of taxes occur. One notable example is the 1986–1988 tax law that lowered the top personal tax rate from 50 percent in 1986 to 37.5 percent in 1987 and to 28 percent in 1988. It is over this time period that Piketty and Saez (2003) report an increase in the share (excluding capital gains) accruing to the top one percent from 9.1 percent in 1986 to 13.2 percent in 1988.

As noted by Reynolds (2007),

> The top 1 percent's share jumped from 9.1 percent in 1985 and 1986, when the top tax rate was 50 percent, to 13.2 percent in 1988 when the top tax rate dropped to 28 percent. That was not a sudden two-year spurt in inequality. It was a sudden increase in the amount of high income reported on individual income tax returns rather than being concealed, deferred, or reported on corporate income tax returns. Dramatic changes in tax laws have changed the way that income has been reported on tax returns over time. (Reynolds 2007, 3)

Tax law changes from 1986 to 1988 altered the relative attractiveness of reporting income on corporate tax returns (C corporation) versus personal tax returns (S corporation) (Piketty and Saez 2003; Reynolds 2007). In the 1970s, the highest marginal personal tax bracket was 70 percent. The tax law change in 1980 lowered the highest personal bracket to 50 percent. Yet

because the corporate tax rate was 46 percent on earnings above $100,000 and less for lower earnings, it was advantageous to report earnings as corporate earnings instead of personal income. However, once the top marginal personal income tax brackets were lowered to 37.5 percent in 1987 and then lowered to 28 percent in 1988, reporting earnings as personal income allowed taxpayers to avoid the relatively higher 46 percent corporate tax rate.

Also according to Reynolds,

> One result is that those attempting to measure incomes by what has been reported on individual tax returns may erroneously view these large increases in income at the top as real changes in [Americans'] incomes. Instead, they were simply the result of a bookkeeping change in the way business incomes were reported. Switching income from corporate returns to individual returns did not make the rich any richer—it simply made more of their income show up as "individual income" in the CBO [Congressional Budget Office] and Piketty-Saez estimates. (Reynolds 2007, 4)

According to Reynolds, this switch of income from corporate to personal, along with a move from stock options and restricted stocks to nonqualified stock options, is responsible for a 4-percentage-points-larger share, or "*more than half* of the apparent increase in the top 1 percent's income share" between 1986 and 2004 (Reynolds 2007, 5; emphasis in original).

Retirement savings and investment income comprise a potentially large portion of household capital income. The structure of tax incentives can implicitly encourage workers with higher incomes to take advantage of tax-deferred savings accounts more than workers with lower incomes, which represented the situation in the United States until the 1970s. Before the 1970s, most interest income and dividends for all but the top executives with qualified investment options were taxed at the individual income tax rate. However, owing to a tax law change in the late 1970s, all workers became eligible for tax-deferred savings accounts. With the creation of tax-deferred accounts such as 401(k)s and 503(b)s, an increasingly large fraction of investment income by non-top earners no longer was reported on individual tax forms. In fact, Poterba (2004) uses the SCF to calculate that, by 1998, those households in the middle income tax

bracket of 28 percent held 32.1 percent of their assets in tax-deferred accounts. In contrast, those households in the top tax bracket held only 12.1 percent of their assets in tax-deferred accounts. With the median dollar held in an account by someone in the 28 percent bracket, this change constitutes a large decline in reported incomes for those non-top income earners.

Section 8. Conclusion

This paper surveys some of the central challenges remaining in accurately measuring the true level of inequality in the United States, such as data limitations and the lack of knowledge regarding dynamic behavioral responses to incentives. For every status quo, there exist several possible counterfactual situations that render causal explanations for increases in inequality difficult to impossible. Against a background of imperfect information, we do find a rather significant growth in absolute levels of individual income throughout the wage distribution as well as a rise in relative income inequality at both the individual and household levels in the United States over the last 40 years. Much of the research supports the idea that inequality in the United States has been driven by the faster rate of increase of household incomes at the top. A holistic account of inequality, however, reveals that the measured increase in income inequality may be overstated by failing to account for increases in nonwage labor compensation and changes to household size and composition. Including the impact of redistribution after taxes and benefits further reveals that these transfers have, on average, lowered inequality in the United States by roughly 11 percentage points vis-à-vis pre-tax measures. Nevertheless, while generally progressive taxation and government transfers have traditionally served to equalize post-tax-and-transfer household income, transfers increasingly accrue to households not at the bottom of the distribution, and the complexity of the taxation system with its numerous deductions and credits has diminished its progressivity. Future

research using tax records is needed in order to better understand the effective level of progressivity in the current tax-and-transfer system in the United States as well as its true contribution to decreasing post-tax-and-transfer inequality.

We also show that household wage inequality measures tend to report higher rates of inequality than personal inequality for a variety of reasons. First, household size has decreased substantially over the past 40 years. Second, employer contributions to healthcare have increased as a fraction of labor income for those in the three middle quintiles while declining for those in the top 10 percent. Third, assortative mating has increased. Higher-earning women have witnessed a smaller decline in marriage, and women in the top ventiles of women's earnings are more likely to marry. In addition, higher-earning men are increasingly married to women who participate in the labor force. Furthermore, these higher-earning men are married to women who earn more than the women married to lower-earning men.

In sum, this survey finds that the drivers of income inequality in the United States are threefold: changes in the labor force composition, changes in household composition, and changes in market returns to skills, with the latter two influences dominating this trend. Increased labor force participation rates of women have reduced labor income inequality on average. Against this background, the expansion of employment opportunities for low-skilled workers could play an essential role in decreasing labor market inequality.

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