

# Growing Income Inequality in the United States and Other Advanced Economies

Florian Hoffmann, David S. Lee, and Thomas Lemieux

**T**he change in US income inequality over the last 40 years is one of the most extensively studied topic in economics. While it is well established that earnings and income inequality have increased sharply in the United States since the late 1970s, the explanations for the increase remain a matter of debate: for some examples in the literature, Goldin and Katz (2007) emphasize changes in returns to education; Acemoglu and Autor (2011) discuss the evolution of skills, tasks, and technologies; Acemoglu and Restrepo (2020) focus on robotization; and Fortin, Lemieux, and Lloyd (2019) consider the contribution of labor market institutions. No single explanation seems to be able to account for most of the growth in inequality. Indeed, the causes of rising inequality may differ across time periods and across middle, upper, and extreme upper income groups.

The purpose of this paper is three-fold. First, it documents key trends in US income inequality since the late 1970s, showing how much of the change comes from labor and non-labor market income. We will look at males and females separately, given the very different evolutions of their labor market participation during this time. In the case of non-labor market income, we focus on capital income in the form of interests, dividends, and (broadly defined) rental income. The empirical analysis is based on data from the March Annual Social and Economic Supplement

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(ASEC) of the Current Population Survey (CPS) that has been collecting information about labor and capital income in a consistent fashion since 1976. To put these findings in context, pioneering work based on tax data by Piketty and Saez (2003) documents a dramatic increase in the concentration of income at the very top of the distribution. This initial evidence indicated that labor earnings were the main source of growth in top incomes. But with the labor share falling (Karabarbounis and Neiman 2014; Autor et al. 2020) and the continuing accumulation of wealth at the very top of the distribution (Saez and Zucman 2016), recent research has suggested that non-labor income has been playing an increasingly important role in inequality growth at the top (Piketty, Saez, and Zucman 2018). By contrast, evidence on the contribution of labor and non-labor income to the growth in income inequality among all income earners remains limited.<sup>1</sup>

Second, we assess the contribution of key explanatory factors, and in particular, education, to the growth in income inequality in the last four decades. While earlier research on income inequality using tax data provides excellent quality information on incomes at the top of the distribution, it contains limited information on the characteristics of tax filers. As a result, it offers little insight on how factors like education and occupation—which have been shown to play a major role in the labor literature—may also be affecting the distribution of non-labor income. Although education only accounts for a modest fraction of the *level* of earnings dispersion, it has been found to play a much larger role in the *growth* in earnings dispersion (Lemieux 2006a; Goldin and Katz 2007; Autor 2014). An important contribution of this paper is to study the connection between education and changes in the distribution of both labor and capital income. We also show that other explanatory factors—occupations, in particular—play a more limited role in inequality growth. This finding is consistent with the large literature showing that changes in the demand for different tasks, including but not limited to routine tasks, have contributed to the evolution of the wage distribution over time (for some entry points to this literature, see Acemoglu and Autor 2011; Autor and Dorn 2013; Firpo, Fortin, and Lemieux 2011; Caines, Hoffmann, and Kambourov 2017; Autor 2019).

Third, we compare the experience of rising US income inequality to other advanced economies. Existing studies show that earnings inequality has increased in Germany, the United Kingdom, and Italy but remained stable in France. We know little, however, about the role of capital income or about the relative contribution of education to inequality in these countries. Contrasting the evolution of inequality, and the source of the changes in inequality, in the United States and other high-income countries is helpful for understanding the factors behind these dramatic changes. In the early sections of this paper, we find that capital income has magnified the growth in US earnings inequality over time as the capital to labor income ratio disproportionately increased among high-earnings individuals. That

<sup>1</sup>Piketty, Saez, and Zucman (2018) look at the evolution of the share of income going to the bottom 50 percent and middle 40 percent of the distribution in addition to the top income shares, but there is a lot of dispersion within these broad groups that has not been as thoroughly studied.

said, labor income remains the main driver of inequality over the last 40 years, and it clearly would be difficult to slow down income inequality growth without addressing the inequality in labor income. We also find that education accounts for over half of the growth in US labor and capital income inequality. Growing income gaps among different education groups have led to a large expansion in between-group inequality, while the growing fraction of highly educated workers increased inequality because of composition effects. Other factors such as changing occupation premia and composition effects linked to the polarization of employment across occupations and space have also been playing a significant role in the growth in income inequality. Turning to large European economies, we show that inequality has been growing fast in Germany, Italy, and the United Kingdom, though not in France. As in the case of the United States, capital income only plays a limited role in inequality growth in these countries. Unlike the United States, income disparities linked to education is not a major factor in the rise in inequality in Europe, with the exception of Germany, where education can account for a substantial, though much smaller, part of the rise in income inequality.

## **Income Inequality Trends for the United States: Data and Measurement Issues**

Our analysis of the trends in income dispersion in the United States is based on the IPUMS files of the March Supplement (ASEC) of the Current Population Survey (CPS) for 1976 to 2019, which collects income information for the preceding year (1975 to 2018).<sup>2</sup> The focus of this paper is on market income exclusive of taxes and transfers. The CPS contains information on net self-employment and wage and salary income over the reference year.<sup>3</sup> We define labor income as the sum of these two income sources. In the case of capital income, we combine income from three variables in the ASEC CPS: interest income; dividends; and rents, royalties, and income from estates or trusts.<sup>4</sup>

<sup>2</sup>For more detail on the IPUMS files, see Flood et al. (2000). Prior to the 1976 survey (income for 1975), the ASEC supplement only collected information at the individual level for heads of household. This is a major limitation because most female workers were not classified as household heads at the time. However, starting the analysis in the mid-1970s is not a significant limitation, given that inequality was relatively stable prior to about 1980.

<sup>3</sup>Smith et al. (2019) show that a large fraction of top incomes consists of entrepreneurial income earned through pass-through corporations (S-corporations and partnerships). Business owners may receive income in the form of wage and salary or business profit. In principle, both of these income sources should be captured in our CPS earnings measures that combine wages and salaries and net business income from the respondent's "own business" (what we refer to as self-employment income).

<sup>4</sup>Note that the ASEC CPS doesn't collect data on realized capital gains. This is a limitation, but for our present purposes not a major one. Many studies on the distribution of broader concepts of income often present results without capital gains (for example, Alvaredo et al. 2013) because of the high volatility of such gains over time, which in turn is linked to the fact investors may be strategic in deciding when to realize these gains.

Although most variables in the IPUMS files are fairly consistent over time, we made a few additional adjustments to the income variables, which are discussed in detail in the online Appendix, available with this article at the *JEP* website. Here, we briefly discuss two important adjustments.

First, for confidentiality reasons, the Census Bureau does not report incomes above a set threshold known as the top code. Between 1976 and 1995, incomes above the top code were simply replaced by the value of the top code (for example, \$99,999 for wage and salary earnings in the late 1980s). Obviously, this made it difficult to use Census data to look at the top of the income distribution. The top coding procedure was improved in the 1996–2010 period by assigning a “replacement value” based on the average income of top-coded observations. After 2010, the Census Bureau moved to a “rank proximity swapping” procedure where high-income observations within a given range (above the top code) are swapped with close-by values and rounded off. Relative to earlier methods, the technique preserves the distribution above the top code and provides more accurate measures of the income distribution. Since then, the Census Bureau has provided swap values for years prior to 2011, which we use to keep income data consistent over time. As discussed in the online Appendix, the top earning shares for the top 1 and 10 percent that we calculate using the CPS are 9 and 34 percent, respectively, which is very similar to the shares found in tax data (see the updated version of the tables and figures from Piketty and Saez 2003, available at <https://eml.berkeley.edu/~saez/TabFig2018.xls>).

While this suggests that the Census Bureau’s rank proximity swapping procedure approximates the upper tail of the earnings distribution reasonably well, it cannot fully adjust for changes in income data collection over time. As this inconsistency only affects the top 1 percent of earners, we trim that part of the distribution to make sure we have comparable measures of inequality over time in the analysis presented below. Note that using swap values remains important even when the top 1 percent is removed, as the fraction of observations with swapped values reaches up to 5 percent of the sample in some years.<sup>5</sup> We also remove observations with abnormally low average hourly earnings—less than \$4 per hour in 2018 dollars—with the cut-off more or less corresponding to half of the real value of the minimum wage over the 1975–2018 period.

Second, income items other than earnings can be severely underreported in survey data (in this journal, Meyer, Mok, and Sullivan 2015). Rothbaum (2015) shows that only about 50 percent of capital income as measured in the national income

<sup>5</sup>The introduction of the computer-based questionnaire for the CPS in 1994 appears to have changed the upper tail of the distribution in a way that the Bureau of the Census rank proximity swapping procedure described above cannot fully account for. The issue is discussed in detail in the online Appendix, available with this paper at the *JEP* website. Note that most women with swapped values are part of the (gender-specific) top 1 percent of earners. In the case of men, however, an average of 3 percent of earners—up to 5 percent in some years—have their earnings replaced with swapped values. As such, removing the top 1 percent of observations doesn’t mitigate the importance of adjusting earnings using the Census Bureau’s swapping procedure.

and product accounts gets reported in the CPS, in contrast with close to 100 percent of wage and salary earnings. Given the large underreporting of capital income, we adjust up reported capital income to match the figures from the national income and product accounts.<sup>6</sup> Note that although household members often share capital investments and their proceeds, the CPS collects information about capital income at the individual level, leaving it up to respondents to divide this source of income among themselves.

We focus our analysis on individuals from ages 25–64 who are working full-time/full-year in the reference year. The rationale for these sample restrictions is that we want to see how capital income contributes to overall income inequality for individuals with substantial labor income and who have been the focus of most of the earnings inequality literature. Many of the individuals under the age of 25 are still in school, and those who aren’t haven’t had much opportunity to accumulate savings. Likewise, most individuals over the age of 64 are retired, and only a modest share of their income comes from labor income. Given the substantially different trends in labor force participation, average earnings, and earnings dispersion for men and women, we follow the literature’s typical practice of conducting the analysis in parallel for these two groups throughout the paper. Summary statistics for the sample, both broken by decade and pooled over all years from 1975 to 2018 using the CPS data, are available in the online Appendix.

As our measure of inequality, we use the standard deviation of the log of income, which is a common metric in this literature. Some studies of inequality use the “coefficient of variation,” which is the standard deviation divided by the mean. However, the distribution of income is of course a variable that is bounded by zero on the left and skewed to the right at the top levels. As a result, the mean will be well above the median. By using the log of income, our measure gives appropriately greater weight to lower and intermediate levels of income.

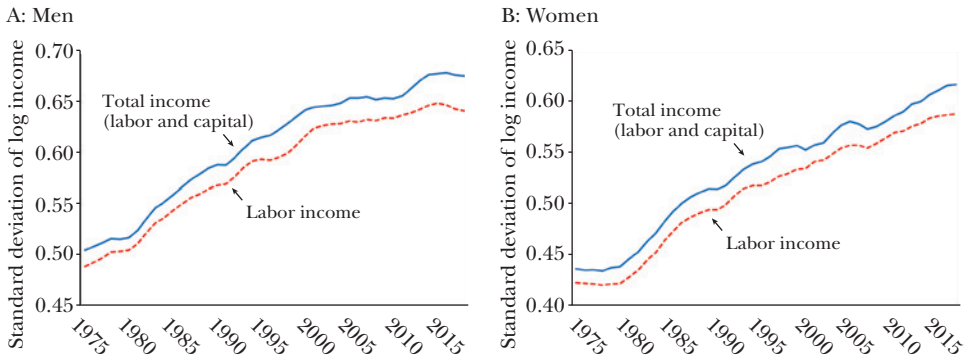
## **Inequality in the United States: Labor versus Capital Income**

We take a first look at the contribution of both labor and capital income to overall inequality by contrasting the evolution of the standard deviation of log labor income and log total income in Figure 1. The gap between the two lines

<sup>6</sup>This adjustment is similar to the approach used by Piketty, Saez and Zucman (2018) to distribute some components of national income to households using a scaled-up version of survey self-reports. The adjustment factors we use are the inverse of underreporting ratios reported in Rothbaum (2015) for 2007–12: 1/.675 for interest income, 1/.695 for dividends, and 1/.274 for rents, royalties, and income from estates or trusts. While underreporting of capital income may be more severe in the upper part of the distribution, adjustments based on comparison of survey responses to aggregate figures—like the one used by Rothbaum (2015)—cannot be used to adjust for this potentially important issue. In the online Appendix, available with this paper at the *JEP* website, we also report inequality trends without this adjustment and discuss other changes in the survey instrument that may have improved the reporting of capital income in recent years.

Figure 1

**Standard Deviation of Log Labor and Total Income**



*Source:* Authors' calculations based on microdata from the March Annual Social and Economic Supplement (ASEC) of the Current Population Survey.

*Note:* The standard deviations are computed for a sample of full-time/full-year workers age 25-64 earning at least \$4 per hour in 2018 dollars. The top 1 percent of the distribution has been trimmed because of inconsistencies in the way earnings at the very top have been collected over time. Labor income consists of net self-employment and wage and salary income. Total income is the sum of labor and capital income (interest income, dividends, and rents). See text for more detail.

represents the contribution of capital income. As mentioned above, these trends are computed for full-time/full-year workers, with the upper 1 percent of the distribution winsorized (that is, trimmed) to maintain data comparability over time. The figures are smoothed using a three-year moving average to facilitate the visual display. Although the three sources of capital income are combined together in this analysis, we note that most of the volatility in capital income is driven by interest and dividend income, with rental income remaining relatively stable over time. As there is no clear trend in the relative contributions of each source of capital income to total income inequality, we combine the three sources of capital income throughout the analysis.

In Figure 1, panel A shows that after growing modestly in the late 1970s, earnings inequality among men grew rapidly in the 1980s and 1990s. Interestingly, inequality then grew at a much slower pace after 2000. These trends are similar to those reported in earlier work (for example, Acemoglu and Autor 2011). Consistent with research based on tax data (for example, Piketty, Saez, and Zucman 2018), while capital income represents a modest fraction of total income, its distribution is substantially more skewed than the distribution of labor income.<sup>7</sup> Adding capital

<sup>7</sup>For our sample as a whole, men and women combined, close to 90 percent of capital income is concentrated among the top 10 percent, with 43 percent going to the top 1 percent. This is similar to findings from the tax data. For example, Saez and Zucman (2016) show that about 90 percent of wealth (or capital income) is held by the top 10 percent, and around 50 percent by the top 1 percent.

income to labor income leads to a higher level of dispersion for overall income (the blue line). Moreover, the contribution of capital income to the standard deviation of total income—the difference between the two curves in Figure 1—grows noticeably over time. The difference in standard deviations—with and without capital income included—grows from 0.014 in 1975–79 to 0.032 in 2014–18. The timing of changes in total income inequality is also substantially different from the ones for labor income only. The growth in total income inequality in the 1980s and 1990s is almost entirely driven by the increase in labor income inequality. By contrast, after year 2000, capital income plays an increasingly important role in overall inequality. These trends are qualitatively similar to studies of top incomes that have shown that while the increase in top shares was almost entirely driven by labor income in the 1980s and 1990s (as in Piketty and Saez 2003), capital income has been playing a more important role in recent years (as in Piketty, Saez, and Zucman 2018).

While trends for women shown in Figure 1b are generally similar to those for men, a few differences are worth noting. First, income inequality among women is completely flat in the late 1970s. A natural explanation for this difference relative to men is the minimum wage that was increasing during this period and had a larger impact on the inequality for women relative to men (DiNardo, Fortin, and Lemieux 1996; Lee 1999). Second, unlike in the case of men, earnings inequality among women keeps growing steadily after 2000. A possible explanation for this difference that we explore in the next section is that as the fraction of full-time/full-year women has been growing substantially over time, the composition of this group has also been changing in a way that resulted in more inequality.

Although we follow the literature in conducting the analysis separately for men and women, we note that inequality for men and women combined did not grow as fast as for men and women considered separately. To a great extent, this was driven by the decline over time in the between-group component of inequality linked to the gender gap.<sup>8</sup>

We further decompose the gap between labor income inequality and total income inequality into two components. The first is the *idiosyncratic* component, which represents the fact that individuals may have differing levels of capital income, even if they have the same labor income. The second is a *labor-correlated* component, which measures the extent to which total income inequality is magnified by the fact that higher-earning individuals tend to receive a larger share of total income from capital sources because higher-earning individuals would be expected to hold greater wealth, and thus, receive a higher share of their total income from capital sources.<sup>9</sup>

<sup>8</sup>This is illustrated in online Appendix Figure A1, available with this paper at the *JEP* website, which shows that the standard deviation of log total income grew by 0.12 between 1975 and 2018 for men and women combined, compared to 0.17 for men and 0.18 for women considered separately. However, we don't present results for men and women combined in the remainder of the paper, as doing so would complicate the decomposition exercises where we would have to keep track of how the different factors like education, occupations, parental roles, and others also affect the gender gap.

<sup>9</sup>Define total income  $Y$  as the sum of labor ( $Y_L$ ) and capital income ( $Y_C$ ). Log total income can be written as:



The evolution of these two components are shown in Figure 2. As in Figure 1, it is clear that the growing dispersion in labor income accounts for most of the increase in the variance of total income. At the same time, for both men (Figure 2, panel A) and women (Figure 2, panel B), the importance of the variance in the *labor-correlated* component of capital income increases steadily over time. This is directionally consistent with the finding of Piketty, Saez, and Zucman (2018) that capital income as a share of total income has disproportionately increased at the very top of the distribution. There is also some modest growth that is less pronounced in the *idiosyncratic* variation in capital income, indicating that capital income is getting more unevenly distributed conditional on labor income. Finally, the figure shows that labor income inequality is the main driver of the growth in the variance of total income until about 2000, at which point capital income becomes increasingly more important in accounting for total income inequality growth. For instance, after 2000, in the case of men, the *idiosyncratic* and *labor-correlated* components of capital income variance account for 15 and 24 percent of the growth in total income inequality, respectively.

In short, the growth in capital income inequality has been a nontrivial contributor to the growth in total income inequality over the last two decades, primarily driven by the fact that high-earnings individuals increasingly have a higher fraction of their incomes coming from capital income. This pattern of inequality change in the overall population of earners mirrors the findings of Piketty, Saez, and Zucman (2018) for the very top percentiles of earners, which indicates that the contribution of capital income in growing inequality extends beyond the very top of the distribution.

That said, the perspective provided by Figures 1 and 2 makes clear that the long-run growth in total income inequality over the past several decades is driven primarily by growth in the labor income inequality. In fact, using the trends in labor income inequality to proxy for the magnitude of the growth in total income inequality does a reasonable job, whereas the same could not be said about the trends in capital income inequality. With this as context, we take advantage of the rich set of individual characteristics available in the CPS data to look at the contribution of various factors, and education in particular, in the growth of total income inequality.

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$$\log(Y) = \log(Y_L + Y_C) = \log(Y_L) + \log(1 + r) \approx \log(Y_L) + r,$$

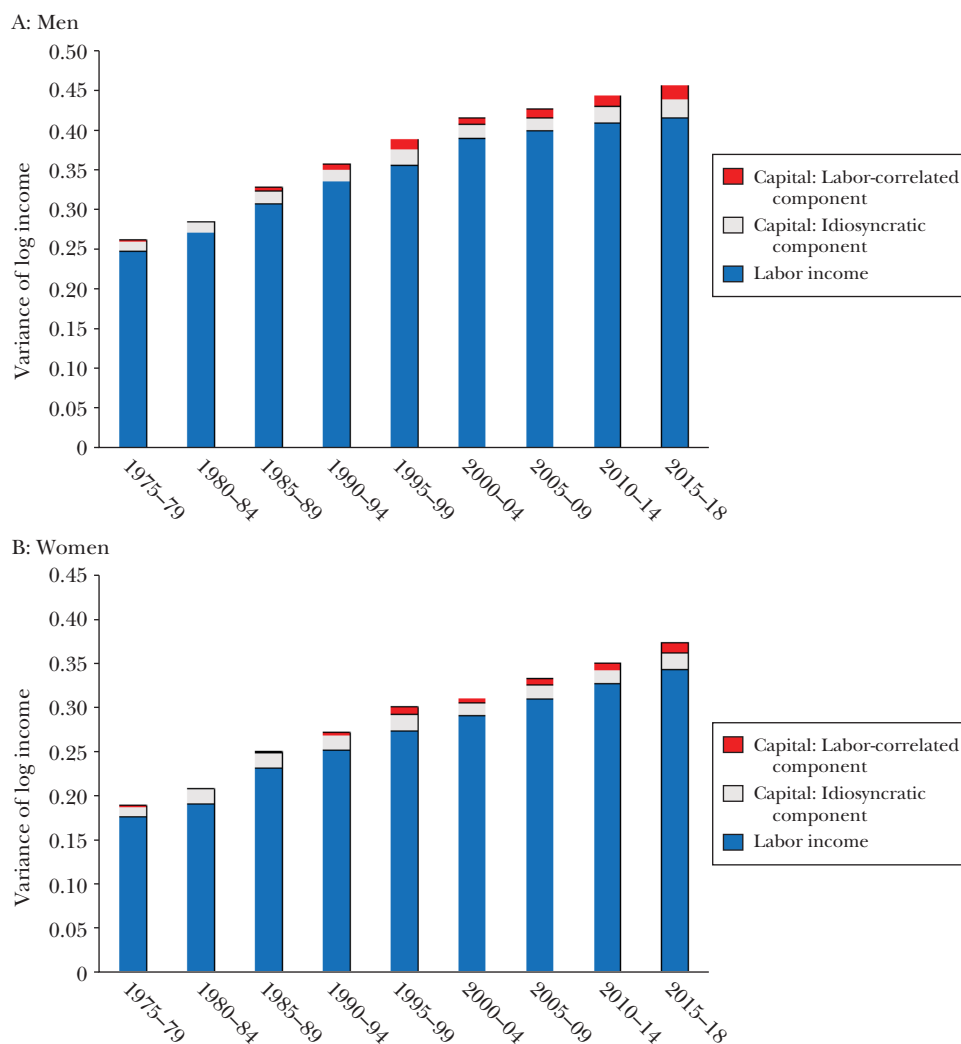
where  $r = Y_C/Y_L$  is the ratio of capital to labor income, and we use the fact that  $\log(1 + r) \approx r$  for small values of  $r$ . To simplify the exposition, we replace  $\log(1 + r)$  with  $r$  hereinafter, but we do keep using  $\log(1 + r)$  for computations. We also use small caps to denote the log incomes  $y = \log(Y)$  and  $y_L = \log(Y_L)$ . The contribution of these two factors to total income dispersion can be formally obtained using a variance decomposition:

$$\text{Var}(y) = \text{Var}(y_L) + \text{Var}(r) + 2 \text{Cov}(y_L, r).$$

$\text{Var}(r)$  is the idiosyncratic component that captures variation in capital income that is unrelated to labor income;  $2 \text{Cov}(y_L, r)$  is the labor-correlated component that captures the systematic relationship between  $r$  and labor income.



Figure 2

**Variance Components of Total Income (Labor and Capital)**

Source: Authors' calculations based on microdata from the March Annual Social and Economic Supplement (ASEC) of the Current Population Survey.

Note: See the note to Figure 1 for details on the sample. The *idiosyncratic* component of capital income reflects the variation in capital income among individuals with the same labor income. The corresponding variance component is computed as the variance of the ratio of capital to labor income. The *labor-correlated* component of capital income captures the extent to which total income inequality is magnified by the fact that higher-earning individuals tend to receive a larger share of total income from capital sources. The corresponding variance component is computed as (twice) the covariance between log labor income and the ratio of capital to labor income. See text for more detail.

## The Role of Education in Inequality Growth

Rates of returns to education have increased substantially since the late 1970s. In their highly influential study, Katz and Murphy (1992) link the sharp growth in the college wage premium during the 1980s to a deceleration of the growth in the relative supply of college education in an era where the relative demand for highly educated workers was increasing. Numerous other studies have shown that the returns to education kept increasing after the 1980s (for example, Card and Lemieux 2001; Goldin and Katz 2008; Acemoglu and Autor 2011; Autor 2014). Fewer studies have sought to quantify the contribution of education to the overall growth in income inequality, but those studies suggest that it may have played a disproportionately large role in the growth in dispersion of earnings. For instance, Lemieux (2006a) and Goldin and Katz (2007) find that at least one-half of the growth in earnings dispersion can be connected to growing returns to education. The twin goals of this section are to evaluate whether this finding still holds when using more recent data and whether education plays an important role in the dispersion of both labor and capital income.

The CPS data give us the ability to look at how income varies with respect to “groups” defined by education, age, or labor market experience, as well as occupation or industry, and how income for those groups evolves over time. For any defined grouping, we can decompose overall income dispersion into three components: (1) *between-group* inequality, (2) *within-group* inequality, and (3) *composition* effects. The literature uses these concepts to decompose the change in inequality over time. An example of rising *between-group* inequality is when the income gap between high- and low-educated workers widens, which naturally will lead to increases in the gap between high- and low-income workers overall. Rising labor market returns to education will increase the between-group component of inequality when groups are defined by education.

Rising *within-group* inequality occurs when the gap between high- and low-income workers widens even for people in the same “group.” For example, there is a fair amount of variability in income among workers who have a college degree, potentially driven by varying quality of the college education itself. So a growing demand for workers from colleges of higher quality could be driven by increases in *within-group* inequality.<sup>10</sup> Another possible source for growing within-group dispersion among college-educated workers is that the demand for their skills may be growing unevenly across space. For instance, Autor (2019) shows that the college wage premium has grown much faster in high- relative to low-density urban areas. Autor also shows that this phenomenon is connected to a faster growth in the

<sup>10</sup> See Lemieux (2006a) for a formal exposition of this argument in a context where returns to education are heterogenous across individuals. If school quality is the source of heterogenous returns, an increase in the demand for effective education skills (both quantity and quality) will lead to an increase in both the college–high school gap and in earnings dispersion among college-educated workers.

demand for high-skill tasks (professional, technical, and managerial occupations) in high-density urban areas.

Finally, *composition* effects arise simply because, if over time, there are more and more people in groups that tend to have more *within-group* dispersion, this by itself will increase overall income inequality. For example, over the past several decades, there has been a steady shift in the proportion of the workforce from lower to higher education levels, which then would tend to lead to more inequality because income is more dispersed among highly educated workers (Lemieux 2006b).

We capture these three potential contributions of education to the growth in the variance of log income using a variance decomposition. We illustrate the results in Figure 3, again dividing into men and women workers. Groups used for the decomposition are formed using five education groups and eight age groups, which in this literature are often used as a proxy for the level of job experience. Note that in the case of between-group inequality, we compute the contribution of both education- and experience-related wage differentials to inequality growth. Within-group inequality is broken down into a base component capturing income dispersion among individuals with less than a college degree—the “high school” group—and the difference in within-group inequality between those with or without a college degree. The latter represents the contribution of education to the growth in within-group inequality.<sup>11</sup>

Figure 3 shows that within-group dispersion (represented by the bars labeled “within for HS” and “effect of education on within”) accounts for most of overall income dispersion during each time period. The “within for HS” bar represents the within-group variance for the high-school group, while the “effect of education on within” bar reflects that the within-group variance for college-educated workers is

<sup>11</sup> For a sense of our approach, consider a Mincer-type log income regression where  $C$  is a dummy for college,  $\delta$  is the return to college, and  $u$  is an error term capturing unmeasured ability and, as discussed above, college quality or differences in returns to college across space:

$$y = \delta C + u.$$

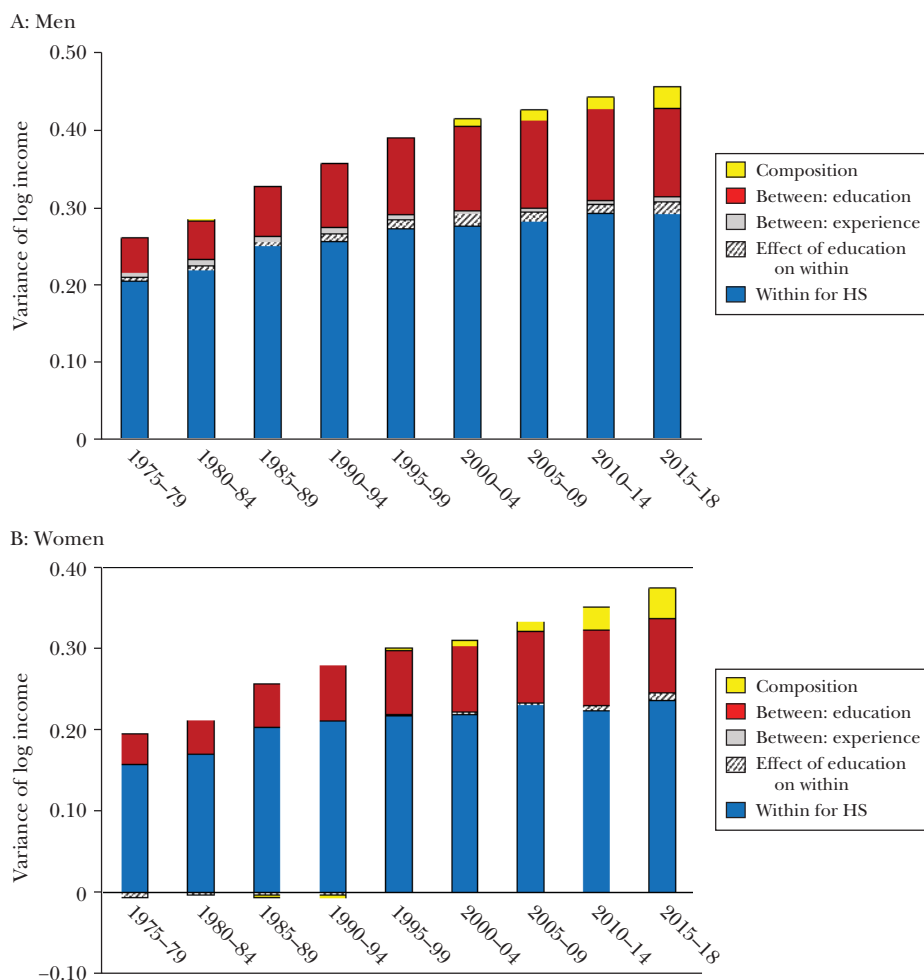
Let  $\theta$  represent the fraction of individuals with a college degree,  $\sigma_C^2$  represents the variance of  $u$  among college-educated individuals, and  $\sigma_H^2$  represents the variance of  $u$  among high school-educated individuals. The variance of income can be written as the sum of the between-group component,  $\delta^2\theta(1-\theta)$ , and within-group component,  $\theta\sigma_C^2 + (1-\theta)\sigma_H^2$ . Adding a time subscript and re-arranging terms yields:

$$\text{Var}_t(y) = \delta_t^2 \theta_t(1-\theta_t) + \theta_t(\sigma_{Ct}^2 - \sigma_{Ht}^2) + \sigma_{Ht}^2.$$

When looking at changes in the variance from a base period 0 to time  $t$ , the contribution of the three factors discussed in the text can be obtained as follows. To compute the contribution of composition effects, we replace the college share  $\theta_t$  by its value in the base period,  $\theta_0$ , which amounts to re-weighting college workers using the reweighting factor  $\theta_0/\theta_t$ . For between-group effects, we recompute the equation by replacing  $\delta_t^2$  with  $\delta_0^2$ . For within group effects (excess growth for college relative to high school-educated individuals), we replace  $\sigma_{Ct}^2 - \sigma_{Ht}^2$  with  $\sigma_{C0}^2 - \sigma_{H0}^2$ . After having done these adjustments, the only source of growth left in the variance is the change over time in the within-group variance of high school-educated individuals ( $\sigma_{Ht}^2 - \sigma_{H0}^2$ ), which represents the baseline change if education played no role in the change in inequality. While in the text we only use two education groups to simplify the exposition, in the empirical analysis we use five education groups (high school dropouts, high school graduates, some college, college graduates, and college post-graduates). As a proxy for shifts in experience levels, we also control for age, using dummies for five-year age categories going from 25–29 to 60–64.

Figure 3

### Sources of Change in the Variance of Log Total Income



Source: Authors' calculations based on microdata from the March Annual Social and Economic Supplement (ASEC) of the Current Population Survey.

Note: See the note to Figure 1 for details on the sample. The within for HS component is the variance of log total income among high-school graduates (individual with less than a college degree). The effect of education on within component is the difference between the variance of log income for college and high-school graduates. The between: experience component is the between-group variance linked to experience-related wage differentials. The between: education component is the between-group variance linked to education-related wage differentials. The composition component represents the change in the variance of log total income linked to changes in the distribution of education and experience relative to the base period (1975-79).

larger; this latter component, especially in the earlier time periods like 1975-79, is relatively small throughout the entire period. As is well known—for example, from Juhn, Murphy, and Pierce (1993)—within-group dispersion grew substantially

during the 1980s, accounting for a substantial share of the growth in the variance of income. However, most of the growth in within-group dispersion stopped after the 1985–89 time period.

By contrast, between-group dispersion (the red and grey bars) grew over the entire 1975–2018 period. Almost all of the between-group dispersion at a given point in time is linked to education (the red bar) rather than experience (the gray bar). The size of this education-related variance component more than doubled: for men, from 0.045 in 1975–79 to 0.115 in 2015–18; for women, from 0.038 in 1975–79 to 0.091 in 2015–18. Figure 3 also indicates that, after 1985–89, this variance component played a larger role in the growth in income dispersion than did the within-group component unrelated to education (baseline within-group dispersion for high school-educated workers).

Figure 3 reveals that most of the inequality growth after 1985–89 is due to the sum of three variance components linked to education: 1) the *between-education-group* dispersion (the red bar), 2) the growth in *within-group* inequality for college-educated workers *over and beyond* the growth in the within-group inequality for high school-educated workers, and 3) finally, particularly starting in 2000, *composition* effects linked to the shift from high school-educated to college-educated workers.

We quantify the role of education in inequality growth by showing the contribution of each variance component in percentage terms in Table 1. For the entire 1975–79 to 2015–18 period, we show the decomposition both for total income and labor income only. The results are very similar, indicating that education makes a similar contribution to the growth in total income or labor income only (a figure showing the labor income decomposition by five-year intervals is also available in the online Appendix, available with this article at the *JEP* website). Table 1 confirms that most of the growth in income inequality over the 1975–79 to 2015–18 period—56 percent for both men and women—is connected to education. The fraction grows even higher—around 70 percent—when only focusing on changes that occur after the late 1980s. Most of the contribution of education is due to the between-group component and composition effects, with the effect of education on within-group dispersion playing a more minor role. Composition effects play a more significant role for women, while the growth in the between-group component is larger for men. The former is not surprising since the composition of the female workforce has dramatically changed over time, with the fraction of women with a college degree increasing from 0.192 in 1975–79 to 0.469 in 2015–18. The growth in the educational attainment of men has been more moderate, with the fraction of college-educated workers going up from 0.246 in 1975–79 to 0.393 in 2015–18. Because within-group dispersion is now higher among college than high school graduates, the faster growth in college-educated labor among women leads to larger composition effects. We also note that while the composition effects reported here combine the contribution of education and experience, 80 percent of composition effects for men and 87 percent of composition effects for women over the 1975–1979 to 2015–2018 period are due to education only.

Table 1

**Contribution (in %) of Education and Other Factors to the Growth in the Variance of Total Income**

|                      |                | Contribution of education |                       |                                  |                        |
|----------------------|----------------|---------------------------|-----------------------|----------------------------------|------------------------|
|                      | Within<br>(HS) | Between:<br>experience    | Between:<br>education | Education<br>effect on<br>within | Composition<br>effects |
| <b>A. Men</b>        |                |                           |                       |                                  |                        |
| <i>Total income:</i> |                |                           |                       |                                  |                        |
| 1975–79 to 1985–89:  | 67.8           | 2.3                       | 28.8                  | 0.9                              | 0.2                    |
| 1985–89 to 2015–18:  | 32.2           | –2.0                      | 39.6                  | 8.9                              | 21.4                   |
| Total change:        | 44.4           | –0.6                      | 35.9                  | 6.2                              | 14.1                   |
| <i>Labor income:</i> |                |                           |                       |                                  |                        |
| Total change:        | 45.4           | –0.9                      | 37.5                  | 6.3                              | 11.7                   |
| <b>B. Women</b>      |                |                           |                       |                                  |                        |
| <i>Total income:</i> |                |                           |                       |                                  |                        |
| 1975–79 to 1985–89:  | 74.6           | 0.6                       | 26.2                  | 4.3                              | –5.7                   |
| 1985–89 to 2015–18:  | 27.2           | 0.6                       | 30.1                  | 9.5                              | 32.6                   |
| Total change:        | 42.8           | 0.6                       | 28.8                  | 7.8                              | 20.0                   |
| <i>Labor income:</i> |                |                           |                       |                                  |                        |
| Total change:        | 42.1           | 0.1                       | 30.5                  | 8.3                              | 18.9                   |

*Source:* Authors' calculations based on microdata from the March Annual Social and Economic Supplement (ASEC) of the Current Population Survey.

*Note:* See the note to Figure 1 for details on the sample and the note to Figure 3 for an explanation of the variance components presented in the table.

In summary, most of the growth in labor and capital income inequality can be linked to education. In particular, increasing returns to education lead to a large increase in the between-group component that accounts for around one-third of the increase in the variance of income between 1975–79 and 2015–18. Another important factor linked to education is that since incomes are more unequally distributed among college-educated workers, the growth in the fraction of highly educated workers leads to large composition effects, especially among women. The faster growth in within-group dispersion among college-educated workers also contributed, albeit in a more modest way, to the increase in overall income inequality. If it had not been for factors directly connected to education and increasing gains to education, income inequality would have increased by less than half as much as it did over the last four decades.

## The Role of Occupation, Industry, and Location

In this section, we compare the role of education documented above to that of occupation, industry, and location in accounting for the level and growth of

total income inequality. There is a rich literature looking at how relative changes in the demand for labor by industry and occupation have been important factors in growing returns to education, and to inequality more generally. A group of papers in the early 1990s sought to explain, using skill-biased technical change or related concepts, the monotonic relationship between skill level and earnings changes that was observed during the 1980s. For instance, Bound and Johnson (1992) and Katz and Murphy (1992) use “shift-share” approaches to look at whether the relative growth in industries employing more educated labor has contributed to the growth in the rate of return to education. Other papers such as Krueger (1993) and Berman, Bound, and Griliches (1994) argue that the growing returns to education were primarily due to skill-biased technical change linked to the computer revolution.

Starting in the 1990s, however, inequality growth became increasingly concentrated at the top of the distribution. Furthermore, earnings at the bottom end of the distribution stabilized relative to those earnings in the middle, leading to what Autor, Katz, and Kearney (2006) famously called the polarization of the earnings distribution. This phenomenon is also present in the CPS data used in this paper, which shows that for both men and women, the gap between the 90th and the 50th percentiles grew steadily since the late 1970s. By contrast, all of the growth in the gap between the 50th and the 10th percentiles is concentrated in the 1980s.<sup>12</sup>

Autor, Katz, and Kearney (2006, building on Autor, Levy, and Murnane 2003) conjectured that a more nuanced form of technological change could explain the polarization of earnings of the 1990s: specifically, computerization might have a particularly negative impact on routine tasks that used to be performed by workers in the middle of the income distribution. This insight changed the focus of the inequality literature from industries to occupations, as occupations are much better proxies for the types of tasks performed by workers of different skill levels. Numerous studies have shown that, consistent with the “routine-biased” technical change hypothesis, the distribution of employment across occupations has become increasingly polarized in the United States and other advanced economies (for example, Goos, Manning, and Salomons 2014).

More recently, Autor (2019) introduced an important new dimension to employment polarization by showing that the distribution of occupations performed by workers of different skill levels has changed substantially across place during the last few decades. Autor shows that non-college workers used to disproportionately hold middle-skill jobs—blue-collar production and white-collar office jobs—in densely populated urban areas. These non-college urban workers were hit particularly hard by routine-replacing technical change. Autor shows that this changing distribution of employment over both occupation and space played an important role in inequality growth.

<sup>12</sup>For an illustration of this pattern, see Appendix Figure A3 available with this paper at the *JEP* website.



Trade and globalization may also have contributed to the polarization of the labor market. For instance, Chetverikov, Larsen, and Palmer (2016) find that low-wage earners were significantly more affected by increased Chinese import competition—what Autor, Dorn, and Hanson (2013) called the “China shock”—than high-wage earners.

We measure these developments within our variance decomposition framework by first adding variables for occupation, industry, and location. Our objective here is to assess how much of the rise in income dispersion can be explained by these factors, above and beyond what is already being explained by education. This is accomplished by further refining the groups—which were in Figure 3 limited to education and experience—to reflect additionally occupation, industry, and location. We note that this calculation may understate the full contribution of changing demand by occupation, industry, and location, because it does not capture the part of the contribution that is being mediated through education. We also explore how adding these factors changes the magnitude of the composition effects shown in Figure 3. Like Autor (2019), we use DiNardo, Fortin, and Lemieux’s (1996) reweighting method to compute a shift in the composition of the labor market compared with the counterfactual income distribution that would have prevailed if the distribution of occupation and place had remained unchanged since the late 1970s.

Occupations are coded up using the same nine categories as Autor (2019). In the case of industries, we classify workers into 12 broad categories based on the 1990 Standard Industrial Classification harmonized over time. Regarding the spatial distribution of workers, we use a classification based on whether individuals live in (1) the 15 most populous metropolitan statistical areas, (2) other metropolitan statistical areas, or (3) non-urban areas.<sup>13</sup>

Figure 4 shows the effect of adding more covariates on the between-group variance of total income. The focus on the between-group component explains why the variances reported in Figure 4 are substantially lower than those reported in the previous figures. The baseline (lower blue bar) reproduces the sum of the two between-group variance components based on education and age in Figure 3. For both men and women, adding occupation, industry, and location appears to explain substantially more of the variance in total income at any given point in time. For example, in the case of men, adding these factors raises the total between-group variance component from about 0.05 to about 0.075 in 1975–79, and from 0.12 to 0.16 in 2015–18.

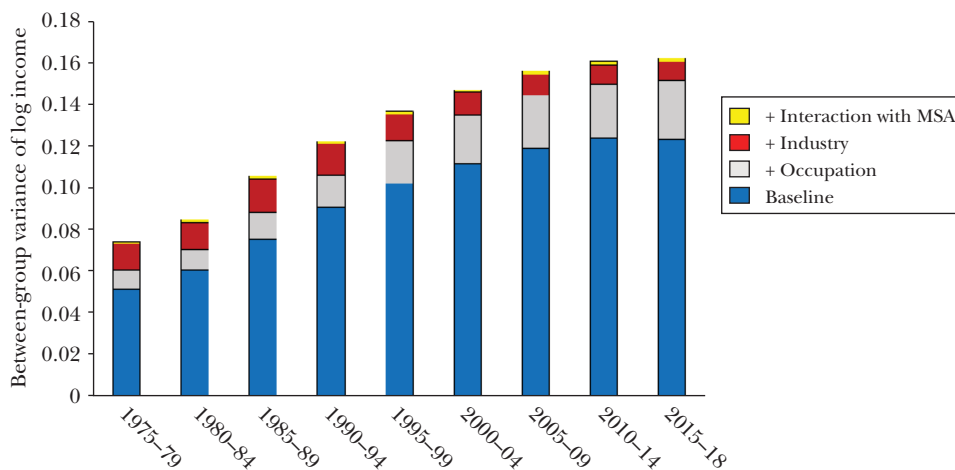
As for how these factors contribute to the overall *growth* in total income inequality, Figure 4 shows two patterns. First, the between-group variance component linked to industry (the red bar) has been declining over time, and changes linked to earnings changes over space are small (as also documented in Autor 2019), compared to the between-group changes linked to education, for example.

<sup>13</sup> Again, for more details on these variables and full methodology behind the calculations, see the online Appendix, available with this paper at the *JEP* website.

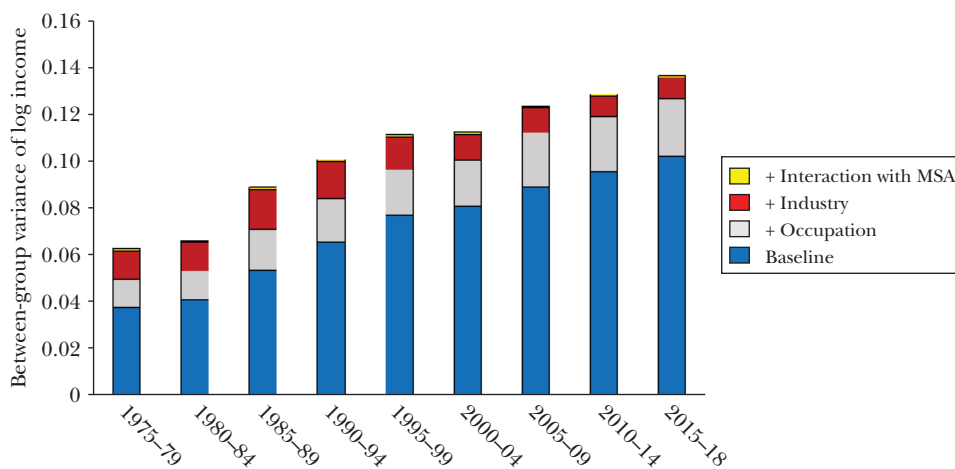
Figure 4

**Effect of Additional Covariates on the Between-Group Variance**

A: Men



B: Women



Source: Authors' calculations based on microdata from the March Annual Social and Economic Supplement (ASEC) of the Current Population Survey.

Note: See the note to Figure 1 for details on the sample. The *baseline* component represents the between-group variance of log total income due to experience- and education-related wage differentials only. The *occupation* component indicates by how much the between-group variance increases when occupation-related wage differentials are taken into account by adding occupation dummies to a log income regression with a full set of education times experience effects. Likewise, the *industry* component indicates by how much the between-group variance increases when industry dummies are further added to the log income regression. Finally, the *interaction with MSA* component indicates by how much the between-group variance increases when a set of MSA dummies and its interaction with occupation, industry, and education dummies are added to the log income regression.

Second, Figure 4 confirms existing findings that occupation wage differentials have been playing an increasingly important role in income inequality growth. Acemoglu and Autor (2011) reach a similar conclusion by including occupation dummies in a Mincer-type equation. Likewise, Firpo, Fortin, and Lemieux (2011) and Fortin and Lemieux (2016) show that either occupation dummies, or characteristics of occupations summarized by tasks measures, contribute to the growth in the between-group variance.

Table 2 quantifies the extent to which the additional consideration of occupation and location can account for the growth in total income inequality. For the sake of brevity, we only show changes over the whole 1975–79 to 2015–18 period. The first row in each panel (A–D) uses only education and age to define the groups, while the second row additionally includes occupation and metropolitan statistical area so that the difference between the two quantifies the importance of the occupational and locational dimension. The first column reports the overall change in inequality, matching the numbers in Figure 2. The second column reports the between-group components of variance as illustrated in Figure 4. It shows that for both men and women, and for the total income (panels A and B) and labor income only measures (panels C and D), occupation and location contribute an extra 0.015 to 0.020 relative to a base of 0.059 to 0.072 explained by education and age alone. The decomposition in Figure 4, with its focus on between-group variance components, did not allow for composition effects. So the third and fourth columns use a re-weighting approach (as was used to produce Figure 3 to compute the composition effects components).

Interestingly, the contribution of the between-group component declines when we add occupation and metropolitan statistical area but is offset to varying degrees by the composition effects. This finding reflects a subtle interaction between the composition of the workforce and the magnitude of the effect of different factors on income. To the extent that returns to high levels of education and high-paying occupations have grown over time, downweighting the importance of these groups by holding the occupational distribution fixed at the 1975–79 level dampens the contribution to the between-group component to the growth in income inequality.

The additional consideration of occupation and metropolitan statistical area seems to make the most difference via composition effects in the case of women, for whom the contribution of composition effects to growth in the variance of total income increases from 0.037 to 0.065. The latter figure represents more than one-third of the growth in the overall variance between 1975–79 and 2015–18. This is consistent with Autor’s (2019) finding that the spatial and occupational polarization of work has played an important role in the secular increase in income inequality.

Although occupation and place play an interesting role in the evolution of income inequality over time for women, in the case of men, they add only modestly to what can already be explained using only education (and experience). The final column of Table 2 reports the ratio of the sum of the components in the third and fourth columns to the first column. It shows that adding occupation and space does

Table 2

**Change in the Variance of Total Income between 1975–79 and 2015–18:  
Contribution of Between-Group and Composition Effects with Different Set of  
Covariates**

|                               |                     | <i>No reweighting</i> | <i>With reweighting</i> |                    |                    |
|-------------------------------|---------------------|-----------------------|-------------------------|--------------------|--------------------|
|                               | <i>Total change</i> | <i>Between-group</i>  | <i>Between-group</i>    | <i>Composition</i> | <i>% explained</i> |
| <b>A. Men, total income</b>   |                     |                       |                         |                    |                    |
| Education*Age                 | 0.1949              | 0.0720                | 0.0689                  | 0.0275             | 49.5               |
| +Occupation*MSA               | 0.1949              | 0.0882                | 0.0627                  | 0.0358             | 50.5               |
| <b>B. Women, total income</b> |                     |                       |                         |                    |                    |
| Education*Age                 | 0.1850              | 0.0647                | 0.0543                  | 0.0371             | 49.4               |
| +Occupation*MSA               | 0.1850              | 0.0750                | 0.0414                  | 0.0650             | 57.5               |
| <b>C. Men, labor income</b>   |                     |                       |                         |                    |                    |
| Education*Age                 | 0.1676              | 0.0616                | 0.0614                  | 0.0196             | 48.3               |
| +Occupation*MSA               | 0.1676              | 0.0764                | 0.0549                  | 0.0274             | 49.1               |
| <b>D. Women, labor income</b> |                     |                       |                         |                    |                    |
| Education*Age                 | 0.1659              | 0.0588                | 0.0508                  | 0.0314             | 49.5               |
| +Occupation*MSA               | 0.1659              | 0.0681                | 0.0379                  | 0.0582             | 57.9               |

*Source:* Authors' calculations based on microdata from the March Annual Social and Economic Supplement (ASEC) of the Current Population Survey.

*Note:* See the note to Figure 1 for details on the sample. The rows labelled *Education\*Experience* indicate the change in the between-group variance due to education- and experience-related wage differentials only. The rows labelled + *Occupation\*MSA* also consider the contribution of occupations interacted with MSA effects. The column *Between-Group with reweighting* shows the change in the between-group variance when the distribution of the explanatory variables (education and experience with and without occupation and MSA effects) is held constant at its 1975-79 level. The *Composition* column shows how much of the increase in the variance is due to changes in the explanatory variables.

not drastically change how much of the growth in the variance of income (about 50 percent) can be accounted for by the between-group component and composition effects. By contrast, the additional explanatory effect of considering occupations plays a more important role for women, raising the percentage from about 50 to 58 percent. This likely reflects the fact that the distribution of occupations has been changing more drastically for women than men over time, with women increasingly moving into high-paying managerial and professional occupations that were dominated by men back in the late 1970s.

## Evidence for Large European Economies

Many of the explanations for the growth in income inequality in the United States, such as those based on technological change and employment polarization, should also apply to other high-income economies. Back in the 1990s, a major challenge to this view was that inequality had only grown modestly, if at all, in most other

advanced economies. For instance, Freeman and Katz (1995) show that, unlike in the United States, inequality was relatively stable in most European economies and Japan during the 1980s. The only notable exception was the United Kingdom where, like in the United States, inequality grew rapidly during the 1980s; indeed, Machin (2011) shows that inequality continued to increase steadily over time in the United Kingdom, albeit at a faster rate during the 1980s. Freeman and Katz (1995) suggest that a combination of differences in national wage-setting institutions and supply factors (especially the rate of growth in highly educated labor) could go a long way towards explaining these differences.

However, more recent studies indicate that earnings inequality has been increasing in several continental European countries since at least 1990. For example, Dustmann, Ludsteck, and Schönberg (2009) use high-quality social security data to show that earnings inequality has been steadily growing in Germany over the last few decades, thereby revising the findings of a stable earnings distribution from earlier studies that were based on the German Socio-Economic Panel (GSOEP) (for example, see Steiner and Wagner 1998). Card, Heining, and Kline (2013) and Hoffmann (2019) offer a further analysis of the growth in inequality in Germany. For Italy, Manacorda (2004) shows that inequality started growing in the late 1980s after a wage indexation mechanism known as the *Scala Mobile* became much less binding. Devicienti, Fanfani, and Maida (2019) show that inequality kept growing steadily in Italy after the end of the analysis period considered by Manacorda (from 1977 to 1993).

We reexamine these trends using the most recently available data for France, Germany, Italy, and the United Kingdom. As in the case of the United States, our focus is on documenting trends for both labor and total income. This presents an empirical challenge because none of these four large European countries collect annual data providing the detailed information about income and individual characteristics that is contained in the US March CPS.<sup>14</sup> In an effort to maximize comparability with the US results, we rely on the Household Budget Survey for France, the Survey of Household Income and Wealth (SHIW) for Italy, the Family Resources Survey (FRS) for the United Kingdom, and the Income and Expenditure Survey (EVS: Einkommens- und Verbrauchsstichprobe) for Germany.

In the case of French, Italian, and UK data, we use the harmonized version of these data provided by the Luxembourg Income Study (LIS 2020) project. However, since the Luxembourg Income Study relies on the GSOEP for Germany, which seems to miss (as discussed above) some of the inequality trends found in high-quality administrative data, we use the EVS data (the Sample Survey of Income and Consumption) provided by the German Statistical Office instead. The EVS data are

<sup>14</sup>Numerous studies of European economies have used rich longitudinal social security data sets to look at labor market inequality, including Dustmann, Ludsteck, and Schönberg (2009); Card, Heining, and Kline (2013); and Hoffmann (2019) for Germany, and Devicienti, Fanfani, and Maida (2019) and Daruich, Di Addario, and Saggio (2020) for Italy. However, these data sets don't provide information on non-labor income and on workers who are not covered by social security (self-employed and public sector workers in Germany).

collected administratively, and among other uses, they determine the consumption basket for the calculation of the official consumer price index and for calculating the income thresholds of unemployment and social insurance. Germany's Federal Statistical Office explicitly highlights its high accuracy. Indeed, Dustmann, Fitzenberger, and Zimmermann (2018), in a study of the evolution of inequality at the household level, find that inequality trends in the EVS track closely those documented in administrative social security data.<sup>15</sup> Two major advantages of the EVS relative to administrative social security data are that they report capital income and that their top-code is high.

We provide more information on these data sets and discuss their limitations relative to the US CPS in the online Appendix, available with this article at the *JEP* website. Two important differences of the European data sets worth mentioning here are: (1) capital income is only collected at the household level, not the individual level; and (2) in the European data sets, full-time status is more frequently available than information about weeks of work and full-year status. We adjust for the first issue by dividing household capital income by the number of individuals age 25–64 in the household. We address the second issue by only keeping years where full-time status is available.<sup>16</sup> Also, to mimic our sample restriction in the US data of keeping only full-time/full-year workers earning more than \$4 per hour, we remove all observations with annual earnings below \$8,000 (\$4 times 2,000 hours a year) in 2018 terms from our European data.

Figure 5 shows the evolution of the standard deviation of log total income in European countries and in the United States. We show the trends starting in 1989, the first year for which European data are available. For the sake of comparability, we use the full-time/over \$8,000 sample criterion in US data, too, instead of the full-time/full-year criterion used in prior tables and figures. Comparing Figures 1 and 5 indicates that the US standard deviation grows somewhat more slowly when using the full-time/over \$8,000 criterion instead of full-time/full-year, though the overall trends remain similar. For example, in the case of men, the standard deviation increases by 0.083 between 1989 and 2018 in Figure 1, panel A, compared to 0.050 in Figure 5, panel A.

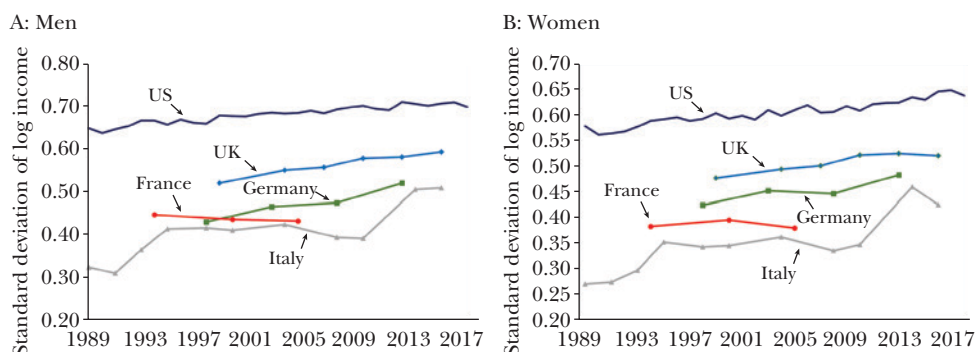
Figure 5 shows that, for both men (Figure 5, panel A) and women (Figure 5, panel B), income inequality has increased in all countries but France since the 1990s. While we are unable to analyze data from France after 2005, other studies using slightly different samples and income concepts have generally found that inequality has remained fairly stable in France since 2005; for example, Boiron (2016) uses the French Household Budget Survey data to study the evolution of income inequality without imposing the full-time/over \$8,000 restrictions and has

<sup>15</sup> More details on the strengths and weaknesses of the different German data sets is provided in the online Appendix, available with this paper at the *JEP* website. Also, we discuss in more detail some new insights on the evolution of inequality in Germany in Appendix B.

<sup>16</sup> Unfortunately, we have to drop the most recent observation (2010) for France and pre-1998 observations for Germany because of the lack of information about full-time status in those years.

Figure 5

# Standard Deviation of Log Total Income in European Countries



*Source:* Authors' calculations based on microdata from the March CPS for the United States, the Household Budget Survey for France, the Survey of Household Income and Wealth for Italy, the Family Resources Survey for the United Kingdom, and the Income and Expenditure Survey for Germany.

*Note:* The standard deviations are computed for a sample of full-time workers age 25-64 with annual earnings of at least \$8000 in 2018 dollars (adjusted for exchange rates in the case of European countries). Total income is the sum of labor (net self-employment and wage and salary income) and capital income (interest income, dividends, and rents). The top 1 percent of the distribution (top 1.5% in Germany for reasons explained in the online Appendix) has been trimmed because of inconsistencies in the way earnings at the very top have been collected over time in the United States. See text for more detail.

access to a wider time period than what is available in the Luxembourg Income Study data. He finds that both the Gini coefficient and the 90/10 ratio as measures of income inequality have been essentially unchanged in France between 2005 and 2013. Thus, France appears to be increasingly an outlier relative to the three other large European economies where inequality has increased rapidly over the last few decades. And although the level of inequality remains higher in the United States, the inequality gap relative to Germany, Italy, and the United Kingdom has declined in recent decades as inequality has grown slightly faster in these three countries than in the United States.

Unlike in the United States, the evolution of total income inequality in Europe is almost entirely driven by changes in the distribution of labor income, and capital income plays a very small role. Indeed, the difference between the variance of total and labor income is an order of magnitude smaller in all European countries than in the United States.<sup>17</sup> With respect to the role of capital income in the

<sup>17</sup>For calculations, see online Appendix Table A2, available with this paper at the *JEP* website. We don't separately show the evolution of labor and total income in Figure 5 to avoid overloading the graphs, but online Appendix Table A3 shows that even when no adjustment is used to reconcile capital income as reported in the March CPS with measures of capital income from the national income and product accounts, capital income still plays a more important role in the United States than in European countries.



Table 3

**Contribution (in %) of Education and Other Factors to the Growth in the Variance of Total Income**

|                        | Contribution of education |                        |                       |                         |                        | Total change<br>(by decade) |
|------------------------|---------------------------|------------------------|-----------------------|-------------------------|------------------------|-----------------------------|
|                        | Within<br>(HS)            | Between:<br>experience | Between:<br>education | Ed. effect<br>on within | Composition<br>effects |                             |
| A. Men                 |                           |                        |                       |                         |                        |                             |
| US: 1985–89 to 2015–18 | 32.2                      | −2.0                   | 39.6                  | 8.9                     | 21.4                   | 0.043                       |
| France: 1994 to 2005   | 13.7                      | −26.0                  | 171.6                 | 40.0                    | −99.2                  | −0.011                      |
| Italy: 1989 to 2016    | 54.3                      | 5.1                    | 7.0                   | 4.8                     | 28.7                   | 0.057                       |
| Germany: 1998 to 2013  | 49.8                      | −0.9                   | 15.7                  | 11.2                    | 24.2                   | 0.060                       |
| UK: 1999 to 2016       | 47.3                      | −2.5                   | −12.6                 | 18.7                    | 49.1                   | 0.048                       |
| B. Women               |                           |                        |                       |                         |                        |                             |
| US: 1985–89 to 2015–18 | 27.2                      | 0.6                    | 30.1                  | 9.5                     | 32.6                   | 0.041                       |
| France: 1994 to 2005   | 373.0                     | −101.3                 | 324.6                 | 163.3                   | −659.6                 | −0.002                      |
| Italy: 1989 to 2016    | 46.0                      | 3.8                    | 9.6                   | 12.3                    | 28.2                   | 0.040                       |
| Germany: 1998 to 2013  | 22.8                      | 5.7                    | 19.2                  | 24.2                    | 28.1                   | 0.039                       |
| UK: 1999 to 2016       | 49.3                      | −5.8                   | −51.2                 | 35.1                    | 72.5                   | 0.025                       |

*Source:* Authors' calculations based on microdata from the March CPS for the United States, the Household Budget Survey for France, the Survey of Household Income and Wealth for Italy, the Family Resources Survey for the United Kingdom, and the Income and Expenditure Survey for Germany.

*Note:* See the note to Figure 5 for details on the European samples and the note to Table 1 for an explanation of the variance components presented in the table. In the case of the United States, we simply reproduce the figures reported in Table 1 for the 1985–89 to 2010–18 period. The column *Total change (by decade)* reports the annualized change in the variance multiplied by 10. Since countries are observed over different time frames, the transformation is used to make the changes in the variance comparable across countries.

rise of earnings inequality, Europe keeps looking much like the United States in the 1980s and 1990s when inequality growth in total income was almost entirely driven by changes in labor income inequality. This suggests a possibility that the contribution of capital income to inequality in Europe may grow in the years to come if high earners—who relatively benefit from the growth in labor income inequality—start accumulating relatively more wealth and receive more capital income down the road.

Another interesting difference between European countries and the United States is that education does not play quite as large a role in inequality growth on the other side of the Atlantic. This is shown in Table 3, which repeats the decomposition reported in Table 1 for all five countries. For France, the percentage changes are difficult to interpret because they are normalized relative to a modest change, especially in the case of women. In the three other European countries, the between-group component linked to changes in returns to education is smaller than in the United States, and is even negative in the United Kingdom. This finding is consistent with Blundell, Green, and Jin (2016), who find that the returns to education did not change much in the United Kingdom in recent years. As in the United States during the 1980s and 1990s, the most important

component of inequality growth in the three European countries besides France is the within-group component among high-school graduates—that is, the “residual” component unlinked to experience and education factors. Composition effects are also quite large in European countries, reflecting the fact that the workers have grown older and more educated in these countries. Germany is, to some extent, an outlier relative to the other European countries. In particular, education has played a substantial role in the rise of earnings inequality. The within- and between-group components combined explain approximately 27 percent of the increase in income inequality over the German sample period, compared to 12 percent for Italy and 6 percent for the United Kingdom. Importantly, the returns to education have increased substantially, accounting for almost 16 percent of the rise in income inequality. In terms of the role that education plays in the evolution of the earnings distribution, Germany thus lies somewhere between the “average” European country and the United States.

A few key messages arise from the comparison of inequality changes in Europe and the United States. First, the sharp US-European divide in whether income inequality is rising at all, documented by Freeman and Katz (1995), no longer holds in recent data, as inequality in three of the four large European economies has been partly catching up to the higher US level of inequality. Second, and unlike in the United States, capital income is not a significant part of the inequality story in Europe—or at least not yet. This is true without reservation for all four European countries we consider in our analysis. Third, with the slight exception of Germany, education doesn’t play as much of a role in inequality growth in Europe, perhaps because the supply of highly educated workers has grown faster in these countries. For example, Blundell, Green, and Jin (2016) discuss this point in the context of the United Kingdom. On the other hand, Germany, as with other trends in labor market outcomes, is becoming more and more the European country that resembles the US experience the most.

## **Concluding Comments**

In an examination of income inequality trends in the United States, the consideration of capital income further accentuates the main story of growing income inequality, as the capital-to-labor income ratio disproportionately increased among high-earning individuals. However, the magnitude of the capital income component is relatively small compared to the predominant source of rising total income inequality, which is labor earnings inequality. Furthermore, various aspects of education—both the gaps between groups defined by education and the growing fraction of highly educated workers—appear to be the predominant force behind the growth in both labor and capital income inequality in the United States, with some role for occupation premia and composition effects linked to the polarization of employment across occupations and space.

Findings for large European economies are more nuanced. While inequality in Germany, Italy, and the United Kingdom grew at least as fast as in the United States in recent years, it remained stable in France. Furthermore, the nature of inequality changes—in particular, the role of capital income and education—was quite different in Europe than in the United States. The modest contribution of capital income to inequality growth in Europe may reflect the fact that US inequality started growing earlier, and has gradually led to an increase in wealth and capital income inequality. Better understanding the nature of the differences in inequality growth in the United States and Europe should be an important priority for future research.

Overall, although the same global forces towards increased inequality appear to be at play in both the United States and Europe, the role of capital income and education in rising inequality remains quite different across countries. Furthermore, the fact that inequality has remained stable in France suggests that country-specific factors can still mitigate other forces pushing toward greater inequality. A detailed investigation of the role of supply, demand, and institutional factors remains essential for understanding similarities and differences in the inequality changes in different countries.

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