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

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*Journal of Economic Perspectives*, Fall (2020)

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THE UNIVERSITY OF
CHICAGO

Econ 350, Winter 2021

- The 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.

# Income Inequality Trends for the United States: Data and Measurement Issues
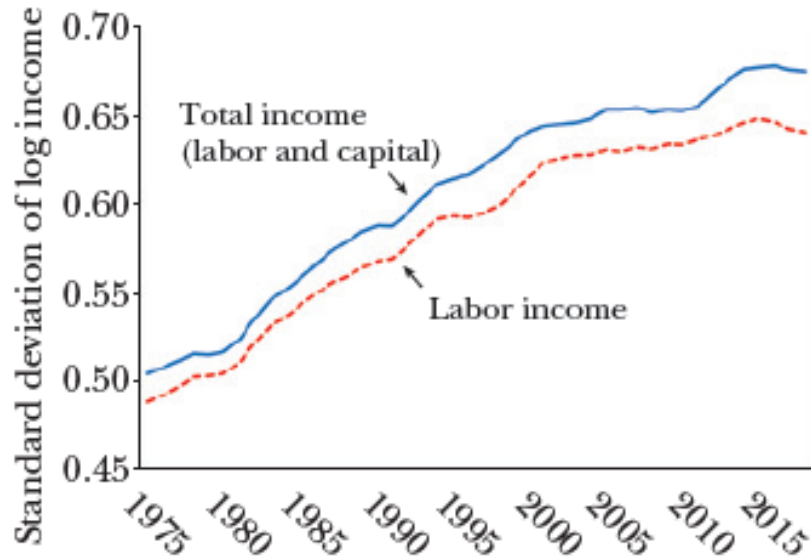
# Inequality in the United States: Labor versus Capital Income

- 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 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.

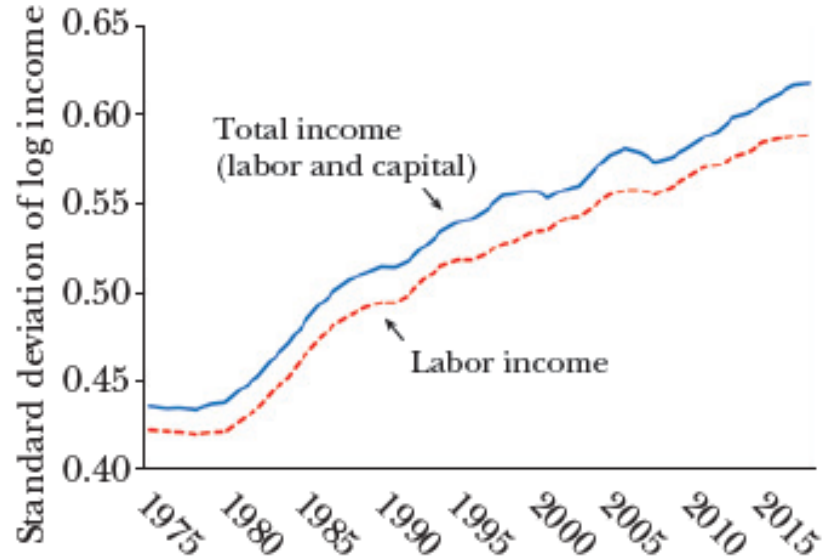- The figures are smoothed using a three-year moving average to facilitate the visual display.

## Standard Deviation of Log Labor and Total Income



A: Men

B: Women

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- 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.

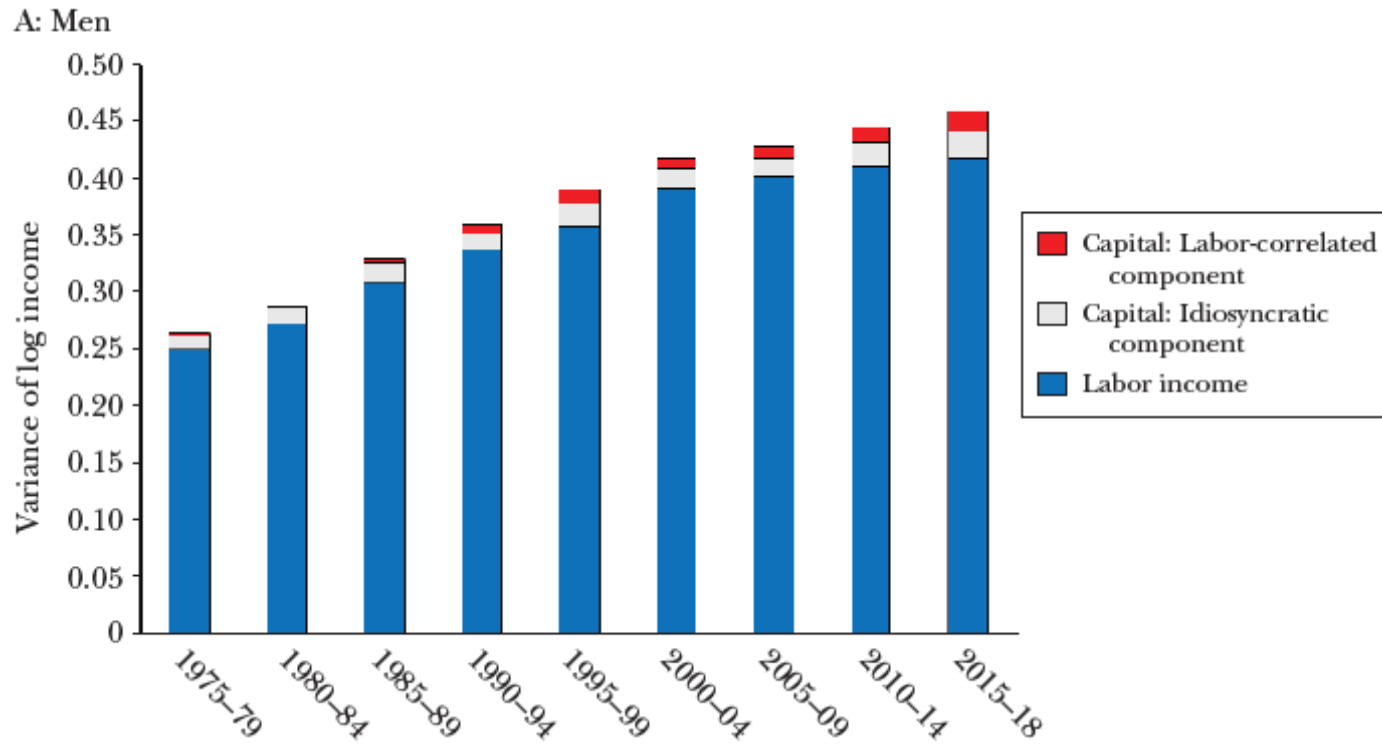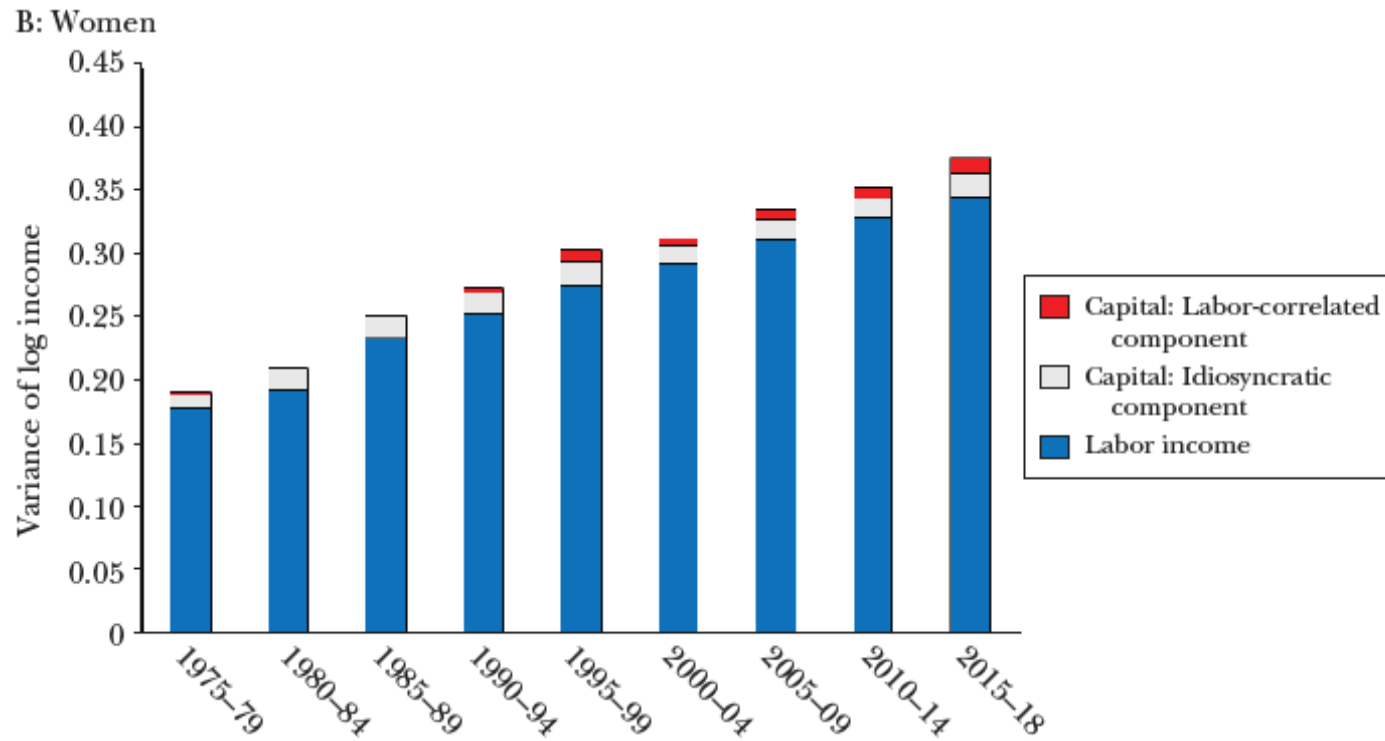# Figure 2: Variance Components of Total Income (Labor and Capital)

B: Women

# 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 kep 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.

- 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.

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

- 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 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 shar of the growth in the variance of income.

- However, most of the growth in within-group dispersion stopped after the 1985–89 time period.

- 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.

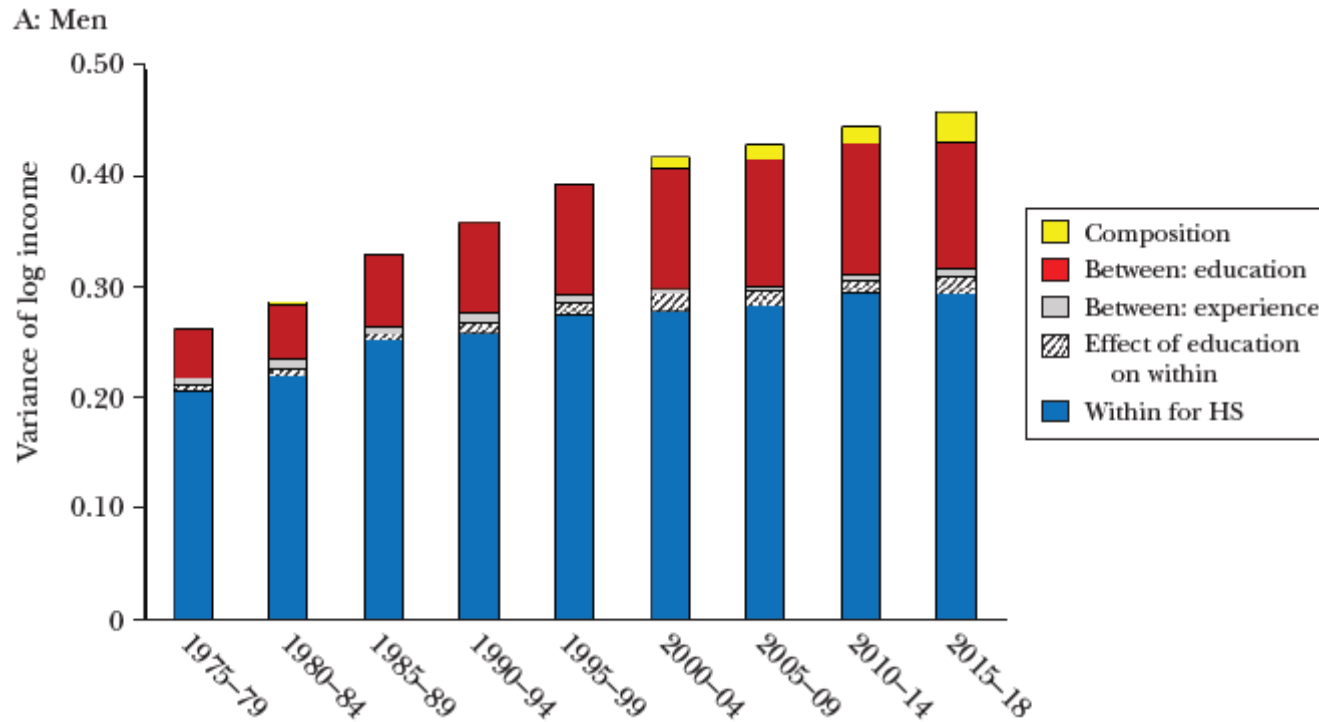# Figure 3: Sources of Change in the Variance of Log Total Income
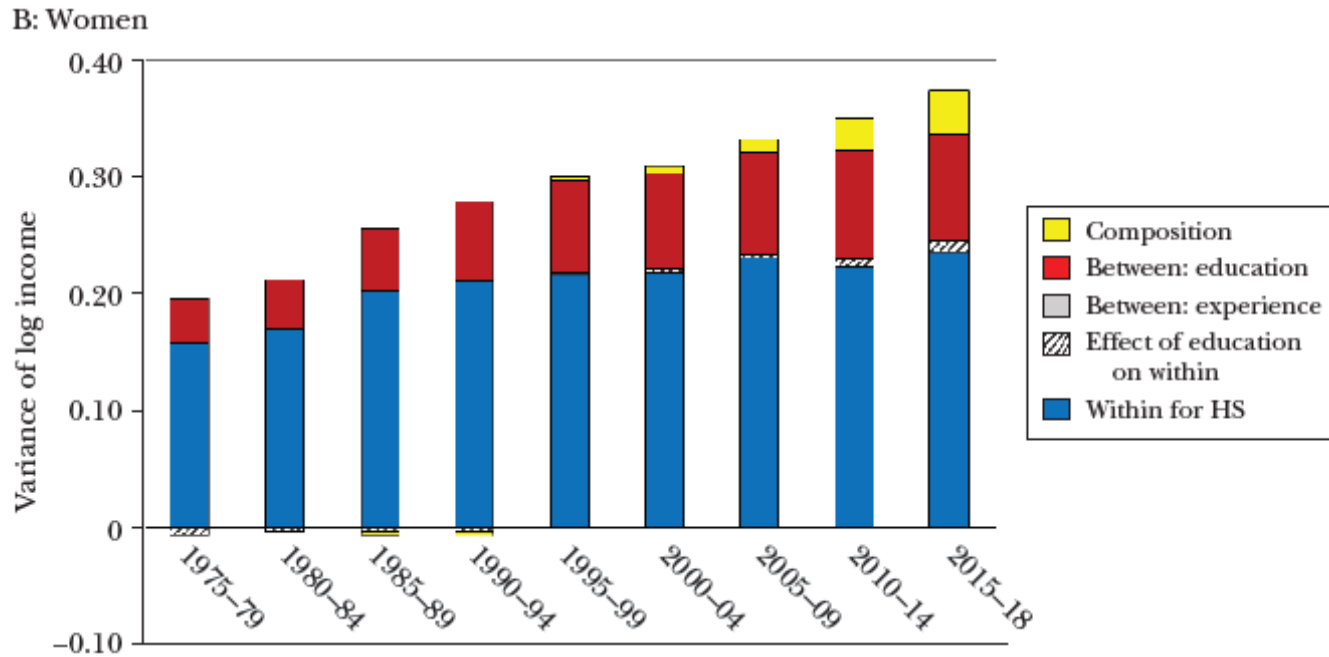


A: Men

B: Women

## Table 1: Contribution (in %) of Education and Other Factors to the Growth in the Variance of Total Income

| | Within (HS) | Contribution of education | | | |
| --- | --- | --- | --- | --- | --- |
| | | Between: experience | Between: education | Education effect on within | Composition effects |
| **A. Men** | | | | | |
| *Total income:* | | | | | |
| 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 |
| *Labor income:* | | | | | |
| Total change: | 45.4 | –0.9 | 37.5 | 6.3 | 11.7 |
| **B. Women** | | | | | |
| *Total income:* | | | | | |
| 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 |
| *Labor income:* | | | | | |
| Total change: | 42.1 | 0.1 | 30.5 | 8.3 | 18.9 |

# 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.

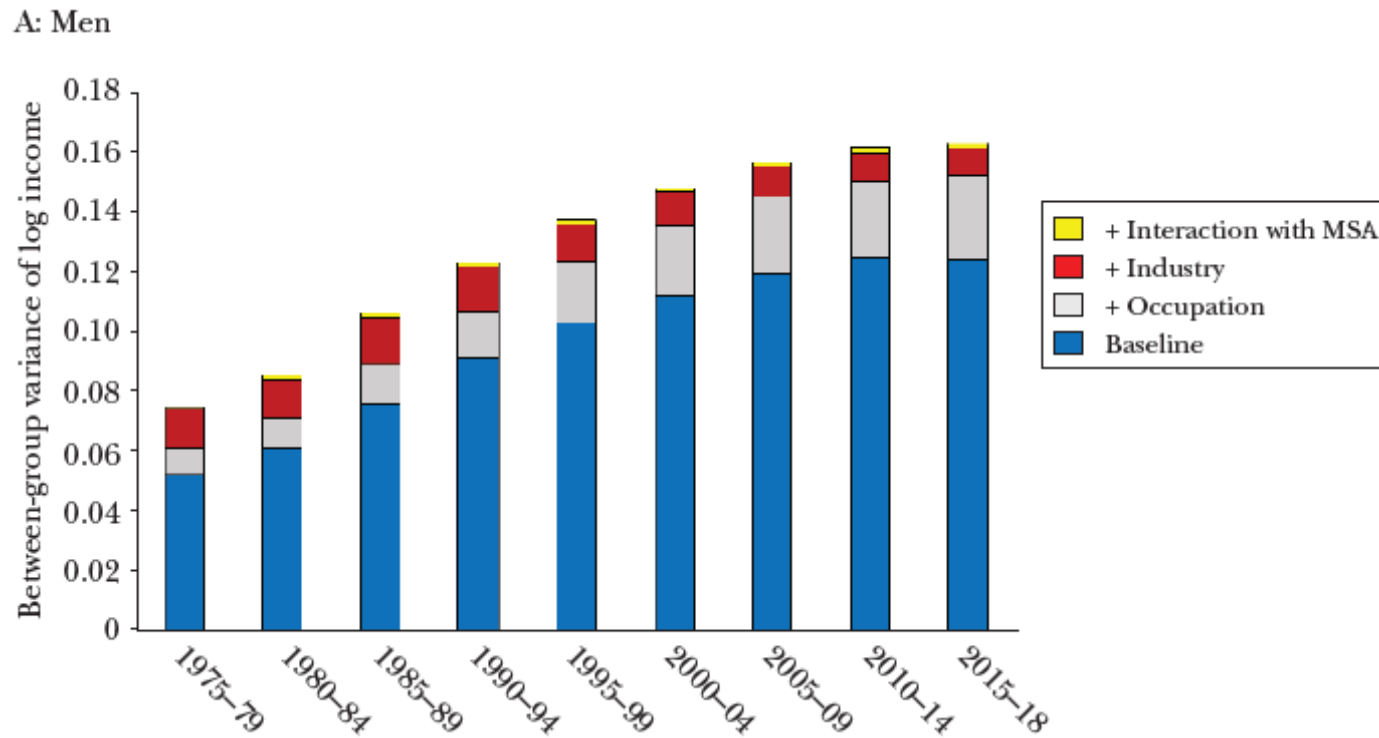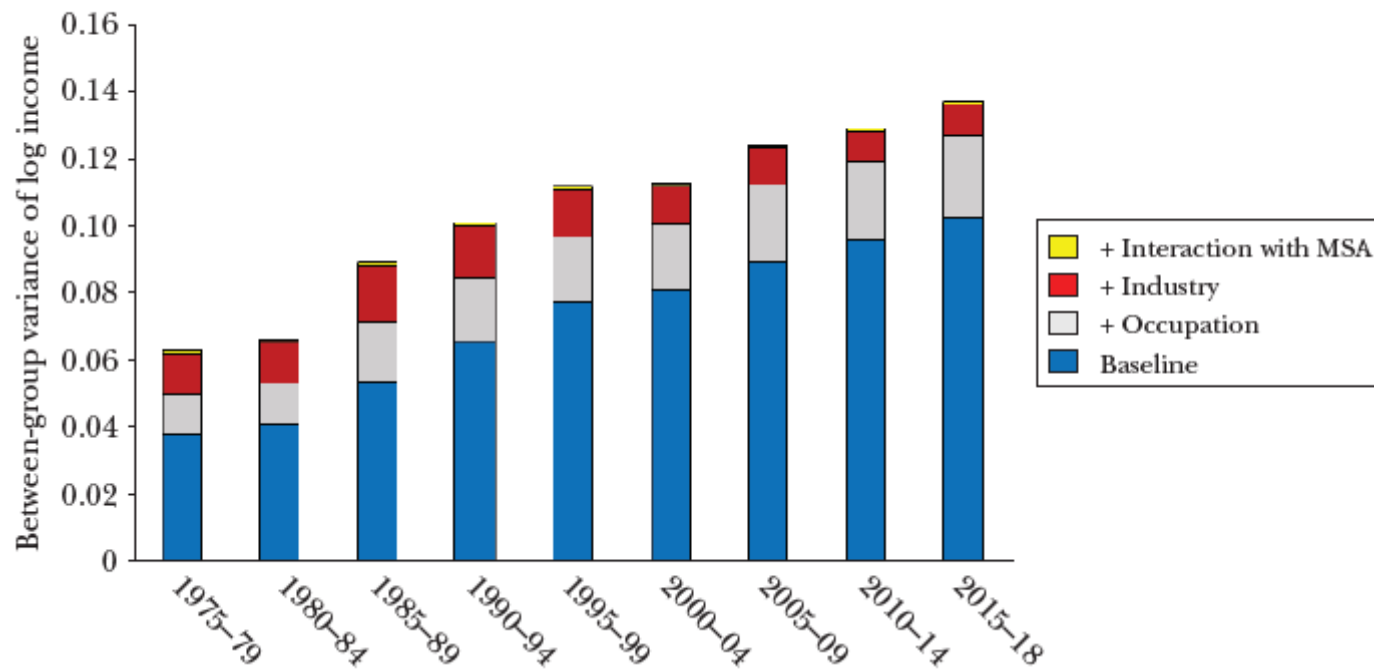# Figure 4: Effect of Additional Covariates on the Between-Group Variance

A: Men

B: Women

- 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.

- 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.

## 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

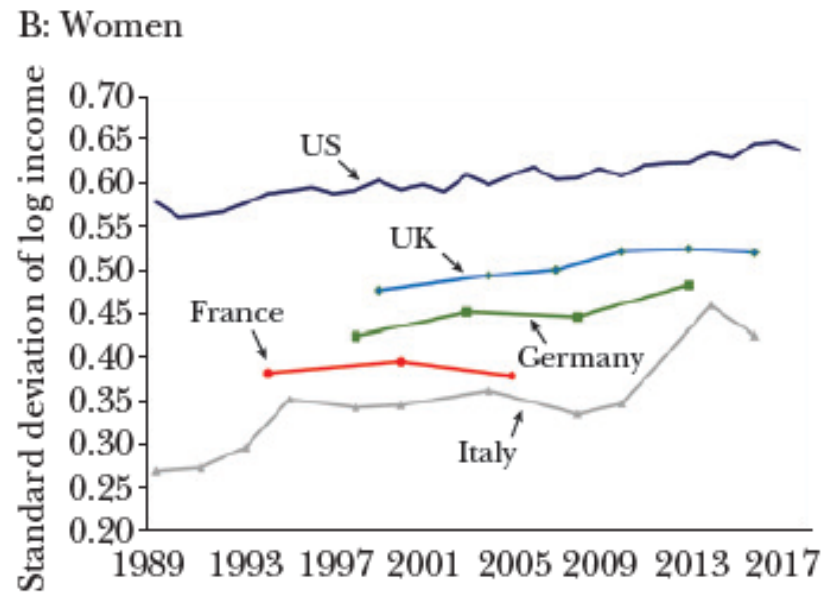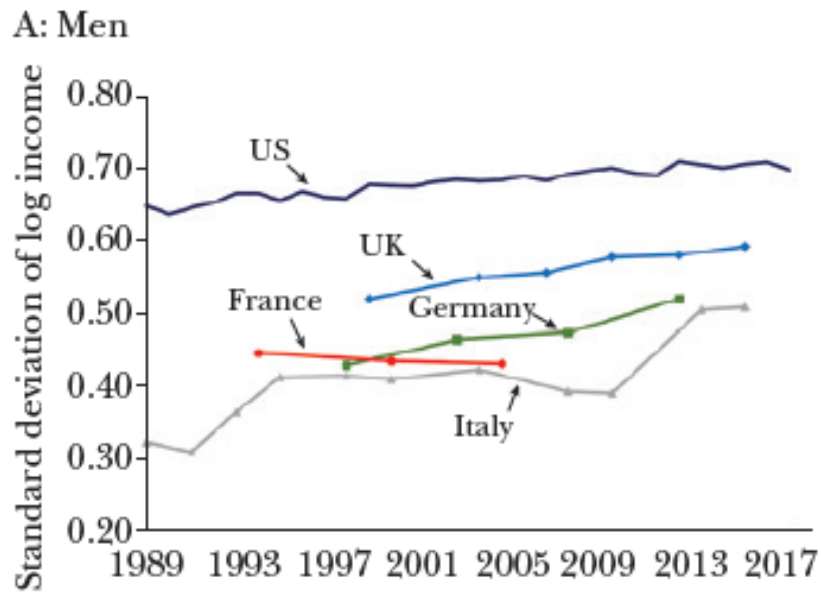| | | No reweighting | With reweighting | | |
| | Total change | Between-group | Between-group | Composition | % explained |
|---|---|---|---|---|---|
| **A. Men, total income** | | | | | |
| Education*Age | 0.1949 | 0.0720 | 0.0689 | 0.0275 | 49.5 |
| +Occupation*MSA | 0.1949 | 0.0882 | 0.0627 | 0.0358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

# **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.

- 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 fulltime/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 an has 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.

- 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.

# Table 3: Contribution (in %) of Education and Other Factors to the Growth in the Variance of Total Income

| | Within (HS) | Between: experience | Contribution of education | | | Total change (by decade) |
| | | | Between: education | Ed. effect on within | Composition 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 |