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Magnitude and evolution of gender and race contributions to earnings inequality across US regions

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Abstract

This paper studies individual characteristics of earnings inequality within the population of blacks and whites in the United States over the period 2005-2017. Beyond education and age serving as a proxy for professional experience, applying a new Shapley income decomposition methodology enables us to isolate and measure two discriminative factors in earnings differences: race and gender. We show that these two factors explain a significant share of total earnings inequality, as defined by the Gini index, for all the geographical administrative divisions used. Whatever the division, the share of earnings inequality associated with gender greatly exceeds that of race. While gender earnings inequality has fallen over time, inequality associated with race has tended to increase since 2010 and is stronger in the Southeast of the country.

Keywords: income inequality, decomposition, Shapley value, racial inequality, gender inequality.

JEL Codes: C71, D63, J15, J71.

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1 Introduction

Race and gender inequality is a hot topic in the United States. A nationwide poll conducted by CNN and the Kaiser Family Foundation in 2015 found that 49% of US citizens think racism is "a big problem" in society today, whereas the figure was "only" 28% in 2011. Also in 2015, a Gallup's Minority Rights and Relations survey showed 67% of Americans supported affirmative action for women while slightly fewer, 58%, for minorities. These issues are not new. Title VII of the Civil Rights Act of 1964 prohibits employment discrimination based on race, color, religion, sex and national origin. In 1965, President Johnson signed an executive order promoting affirmative action that ensured that all applicants and employees would be considered with no distinction of race, creed, color or national origin. Since then, these measures have been strongly criticized by conservatives, and several states have opted to take action against positive discrimination policies in public institutions. The importance that these issues have maintained in public debates underlines the need for convenient indicators that are easy to use by public policy makers.

Existing income decomposition literature most often focuses on decomposing the evolution of income inequality over time or the difference in inequality between two groups (see Fortin *et al.* 2011 for a literature review or Montes-Rojas *et al.* 2017 for a recent application). Our contribution, on the other hand, proposes a practical Shapley decomposition tool that is able to decompose the inequality of income distribution by individual characteristics (hereinafter referred to as attributes). Our methodology has the advantage of not requiring choosing a modality of reference for categorical variables (e.g. level of education, gender or race) known to affect the results (see Oaxaca and Ransom 1999 for a discussion). Moreover, contrary to the distribution decomposition by income sources proposed by Lerman and Yitzhaki (1985), our methodology is suitable for a decomposition by attributes and is applicable to a wide range of inequality indexes: Gini, Theil, Atkinson, etc. Finally, our decomposition does not stand on parametric models and their related hypotheses (as it is the case in Bjorklund *et al.*, 2012). To the best of our knowledge, there is no other decomposition instrument in the literature for carrying out inequality index decomposition by attributes that presently provides all of these advantages. Our contribution is an application of this new Shapley income decomposition methodology in which we concentrate on the discriminatory part of inequalities observed through two subjective factors in income differences - race and gender - that contribute to the inequality in earnings (wages and self-employment revenues), as defined by the Gini index within the population of Blacks and Whites taken together for each of the geographical administrative divisions of the United States over the period 2005-2017.

Literature on racial and gender inequality often concentrate on the income gap between groups, *i.e.* comparing different ethnic groups or women versus men. From this point of view, Sites and Parks (2011), and Couch and Daly (2002) show that racial income inequalities in the United States were significantly reduced following the passage of the Civil Rights Act of 1964 and other measures aimed at reducing labor market discrimi-

nation, but have not changed significantly since 1974, with the Black-White wage gap remaining around 30% to the late 1980s, while a new convergence was observed in the 1990s. More recently, the median annual income of a family in 2014 was $76,658 for whites and $43,151 for blacks, the second-largest ethnic minority after Hispanics (Economic Report of the President, 2016). As a matter of allocation, decades of sociological research has shown that Black-White inequality in local areas is greater where the Black population is relatively large (see, for instance, Huffman and Cohen (2004)). Using the decomposition techniques of Juhn *et al.* (1991), Couch and Daly (2002) found that greater occupational diversity among Black workers partly explained the reduction of the racial income gap during the 1990s. Convergence is partly due to equalization in the attainment of education and experience and also to the distribution of employment across industries and occupations, rather than being a purely ethnic matter. Sections of the literature explain part of the recently observed income inequality by the reduction in unionization rates. Blacks' private-sector unionization rates surpassed those of White workers for decades (see Jones and Schmitt, 2014). Using data from the CPS (1973-2007), Rosenfeld and Kleykamp (2012) showed that African-Americans join unions for protection against discriminatory treatment in nonunion sectors. Private-sector union decline has exacerbated Black-White wage inequality (see also Rosenfeld 2014), especially among female workers. The gender wage gap has been intensively investigated for decades, but still remains an area of active research (see Blau and Kahn, 2017). While the long-term trend shows a significant reduction in the wage gap, convergence has been slower and uneven since the 1990s. Income decomposition methods show that the gender distribution with respect to occupation and industry is the main factor explaining this gap nowadays. Still, gender differences in work interruptions and working times are significant sources of income gaps.

Our contribution differs from the previous literature by concentrating on racial and gender inequality as defined by the contribution of race or gender to overall inequality. In doing so, applying decomposition methods to measure earnings inequality seem to provide an attractive framework for the appraisal of inequality associated to these two characteristics. Among income decomposition methods, those inspired by the Shapley value seem particularly interesting since they provide an explanation of income inequality by determining the contribution of various income sources (*i.e.* labor and capital incomes), or the contribution of different sub-populations to overall inequality.[2] The Shapley decomposition methods developed so far cannot, however, be used to estimate the share of overall wage inequality that is due to a characteristic such as race or gender. In fact, if the two sub-populations are made up of Blacks and Whites respectively, the results of the decomposition will give the contribution of Blacks to overall income inequality on the one hand and the contribution of Whites to overall inequality on the other, *i.e.* inequality observed within each sub-population. But this contribution does not reflect inequality between sub-populations, *i.e.* between Blacks and Whites. Hence, this decomposition framework does not provide for the determination of the contribution of race to income

[2]See Chantreuil and Trannoy (2011, 2013) and Shorrocks (2013) for the definition of the Shapley decomposition rules determining the contribution of different income sources or different sub-populations to overall income inequality.

inequality. In order to make up for this drawback of the "classical" Shapley decomposition rule, Chantreuil and Lebon (2015) extended this framework to a third dimension, namely the decomposition of income inequality by attributes. Defining the earnings received by an individual as the sum of several elements, each element representing the part of earnings resulting from each individual's attribute, the Shapley decomposition rule then offers a simple way to determine the contribution of each of individuals' attributes to overall earnings inequality. Here, the order of attributes matters. Our contribution adds to this latter literature as we do not pre-assume the attributes' ordering.

The Shapley decomposition method enables us to distinguish inequality arising from several attributes, some of which are linked to intrinsic individual productivity such as the length of professional experience - for which age is a proxy - and education level, from inequality linked to discriminative factors such as race and gender. Focusing on the latter, we find that the share of earnings inequality attributable to racial affiliation is about 1% to 4%, depending on the 9 designated divisions of the United States Census Bureau, while the contribution of gender to the total observed inequality in the Black and White populations taken together is much larger, at 9% to 13%. Time comparison shows that the contribution of race to earnings inequality has tended to increase in all administrative divisions over the past decade, whereas that of gender tends to have been decreasing recently.

This paper is organized as follows: Section 2 presents the data and empirical evidence on earnings inequality in the United States over the period 2005-2017, focusing on gender and race. Section 3 outlines the Shapley decomposition methodology according to conditional decomposition. Section 4 analyzes the results. Section 5 empirically discusses the incidence of the ordering of attributes. Finally, section 6 contains some concluding comments.

2 Data and empirical evidence

We used annual earnings, defined as wages plus self-employment incomes in the American Community Surveys (ACS-PUMS, about 1% of the total United States population) from 2005 to 2017[3]. To be able to draw unambiguous conclusions, highlighting the impact of racial factors that can be observed, we limited our earnings inequality study to the comparison of those determined to be Black or White only; we exclude from our analysis other ethnic groups, as well as those Black and White persons that declared themselves as Hispanic.

Individuals are described according to several characteristics: the geographical administrative division where they live (see Appendix A for a list of states per division); their gender; their level of education (lower than high-school certification, high-school graduation plus some college but without a degree-level qualification, undergraduate degree, and

[3]Using the IPUMS-CPS from University of Minnesota with weekly earnings from 1989 to 2015, gives similar results over the period 2005-2015, but it is open to criticism arising from a much weaker sample size.

graduate degree or more); and cohort (one group every 4 years from 25-29 years old up to 60-64 years old).[4] Individuals over 65 years old, or individuals with declared annual earnings below one hour of the federal minimum wage for each year, are dropped from the data set. Finally, individual US states are grouped into 9 regional sub-sets according to the United States Census Bureau's designated divisions. The total sample over the period 2005-2017 is more than 12.3 million observations.

Table 1 shows the distribution of Black and White populations per administrative division together with the 2017 average yearly earnings.

Table 1: Black share and average earnings of Blacks and Whites in 2017

	Black share	**Annual earnings ($)**		**B/W earnings ratio**
		Black	**White**	
New England	8.35%	46,061	71,010	65%
Middle Atlantic	16.89%	46,268	70,552	66%
East North Central	12.74%	38,468	57,025	67%
West North Central	7.66%	37,531	55,527	68%
South Atlantic	27.84%	41,606	62,002	67%
East South Central	21.82%	34,070	51,634	66%
West South Central	22.40%	40,464	63,410	64%
Mountain	6.18%	42,824	59,386	72%
Pacific	10.61%	50,340	74,281	68%
FEDERAL	16.76%	41,632	62,968	66%

Population : Blacks and Whites only, 25-65 years old, employees and self-employed, 2017.
Reading: At the Federal level, in 2017, 16.76% of the Black and White population was Black. Blacks earned on average 66% of Whites' earnings.

In 2017, Blacks accounted for 16.76% of the Black-White population at the Federal level. They earned on average 66% of Whites' earnings. This federal average, however, hides large regional disparities. In line with Huffman and Cohen (2004), Table 1 shows that the Black population earns on average much less than the White population in most administrative divisions where the Black share of (Black and White) population is large. The highest gap is observed in the West South Central division where the Black population is the second highest with a 22.4% share. On the contrary, the smallest gap is observed in the Mountain division, where the Black share is only 6.18%. In this region, Blacks indeed earn 72% of Whites' earnings. New England seems to present a different pattern, with a low share of Black (8.35%) and a Black-White earnings ratio of 65%. This geographical distribution itself hides large disparities, since administrative divisions cover many different states (see Appendix A for the list of states per division). Nevertheless, racial differences consistently disadvantage the Black population.

[4] We exclude individuals between 20 and 24 from our analysis since the sample contains few observations with a graduate degree or more.

Table 2 shows the 2017 average yearly earnings of Blacks and Whites for men and women by administrative division. Here, regional disparities are again noticeable. The highest differences for men are in the New England, Middle Atlantic and West South Central regions, where Blacks earn 58% of Whites' earnings. Concerning Black women, they suffer relatively less than men but the Black-White gap is calculated on much lower earnings. The highest differences are in New England, where Black women earn 76% of what White women earn, and in the East and West South Central regions (78%). In all divisions, Black women get the lowest average earnings, which represents half of what White men earn at the federal level.

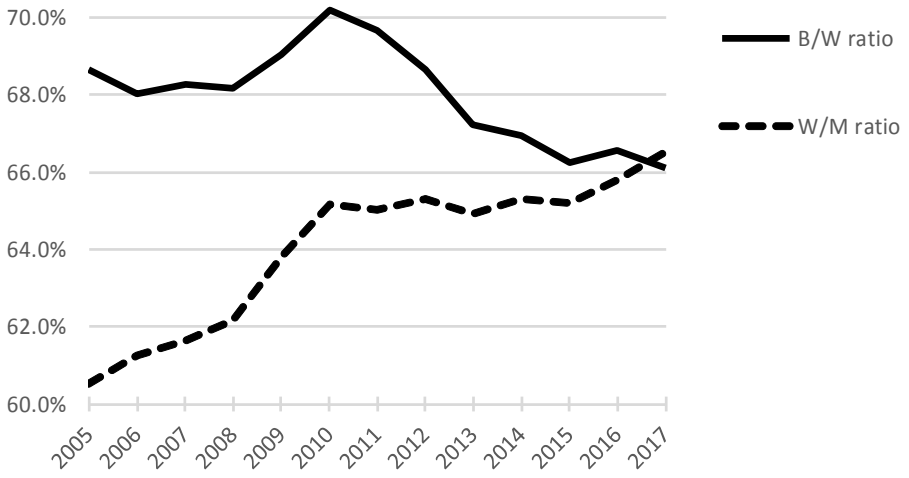
Table 2: Men and women's earnings by race and geographical division in 2017

	Men				**Women**			
Division	**Black**	**White**	**B/W diff**	**B/W ratio**	**Black**	**White**	**B/W diff**	**B/W ratio**
New England	49,202	85,229	36,026	58%	43,112	56,393	13,281	76%
Middle Atlantic	49,103	84,584	35,481	58%	43,799	55,409	11,611	79%
East North Central	41,330	68,886	27,556	60%	36,108	44,128	8,020	82%
West North Central	40,443	66,072	25,629	61%	34,884	44,155	9,271	79%
South Atlantic	44,711	74,160	29,449	60%	39,030	48,612	9,581	80%
East South Central	36,981	61,937	24,956	60%	31,668	40,363	8,695	78%
West South Central	44,798	77,680	32,882	58%	36,729	47,135	10,406	78%
Mountain	45,968	71,252	25,284	65%	38,841	45,674	6,832	85%
Pacific	53,889	87,795	33,906	61%	46,676	58,541	11,865	80%
FEDERAL	44,946	75,549	30,603	59%	38,760	49,079	10,319	79%

Reading: At the Federal level, in 2017, Black men earned on average 59% of White men's earnings. Black women earned on average 79% of White women's earnings, but earnings were much lower for White women than for White men (ratio of 65%) compared to women versus men in the Black population (ratio of 86.2%).

As discussed by Wilson and Rodgers (2016), the Black-White gap has increased since the 2000s. We focus on the recent time period (2005-2017) in order to highlight the change of slope that has occurred since 2010. Figure 1 shows the evolution of the Black-White and Women-Men earnings ratios over time. We can see that since 2010, Black-White earnings differences have increased (the Black-White ratio has deteriorated by about 4 percentage points). The Women-Men ratio increased sharply from 2005 to 2010, then stabilized, and finally increased again from 2015 to 2017, thus showing a clear reduction in Women-Men earnings differences (about 6% percentage points in 12 years).

Figure 1: Black-White and Women-Men's earnings ratios from 2005 to 2017



Concerning education, Table 3 shows that gender differences in the Black-White earnings gap exist for all education levels: they are much smaller for women, and smaller for the less educated. The difference in education level is partly explained by the type of jobs associated with low education levels, which are often paid the minimum wage or close to it. For each education level, women receive lower average earnings, notably Black women.

Table 3: Men and women's earnings by race and education levels in 2017

	Men				**Women**			
Education level	**Black**	**White**	**B/W diff**	**B/W ratio**	**Black**	**White**	**B/W diff**	**B/W ratio**
$<$ High-school degree	27,066	40,028	12,962	67.6%	22,349	24,374	2,025	91.7%
$\geq$ 12th grade, no college degree	37,174	53,253	16,079	69.8%	30,238	33,877	3,639	89.3%
Undergraduate level (2-4 years of college)	56,192	87,284	31,091	64.4%	44,761	52,789	8,029	84.8%
Graduate level ($\geq$ 5 years of college)	87,322	133,476	46,153	65.4%	67,535	78,765	11,230	85.7%

Reading: At the Federal level, in 2017, Black men with less than a high-school diploma earned on average 67.6% of White men's earnings, while Black women earned on average 91.7% of White women's earnings.

This empirical evidence underlines the need to consider gender and education together with the racial component.

3 The income decomposition framework

The decomposition of income inequality into appropriate component contributions usually follows two main paths. The first studies situations in which different sources of total income are examined,[5] while the second considers the influence of population subgroups.[6] For both types of decomposition, the Shapley value has been proved to be useful in many applications;[7] nevertheless, the use of the Shapley decomposition rule by population subgroups such as race or gender does not lead to a clear-cut answer as to the question of the "real" contribution of such individual characteristics. Chantreuil and Lebon (2015) resolved this problem by proposing a solution "*assimilating the different dimensions of the status of individuals to a particular wage source in order to assess the contribution of each status*". We call this proposed framework "income decomposition by attributes".[8]

This method does not, however, deal with a question which remained unresolved in the conditional decomposition: that of the incidence of the ordering of attributes. To properly understand the manner in which distributions associated with each attribute are built, let us consider a brief example. Let us assume 8 individuals ($i = A, B, ..., H$) for whom we know the income w_i as well as two characteristics (also referred to as attributes) x and y, each having two possible modalities ($x = x_1, x_2; y = y_1, y_2$). The income of an individual i can be decomposed in two ways, as follows:

$$w_i = \overline{w}_{x_i} + (\overline{w}_{x_i,y_i} - \overline{w}_{x_i}) + (w_i - \overline{w}_{x_i,y_i}) \tag{1}$$

or

$$w_i = \overline{w}_{y_i} + (\overline{w}_{x_i,y_i} - \overline{w}_{y_i}) + (w_i - \overline{w}_{x_i,y_i}) \tag{2}$$

In equation (1) (respectively eq. (2)), the individual income w_i is written as the sum of three terms:

- the income share associated with observed attribute x (resp. y): the average income of individuals where attribute x takes modality x_i (resp. y_i),
- the income share associated with observed attribute y (resp. x): the difference between the average income of individuals where attribute x (resp. y) takes modality x_i (resp. y_i) and attribute y (resp. x) takes modality y_i (resp. x_i),
- the income share associated with unobserved attributes: the difference between individual i's income and the average income of individuals presenting the same modalities as individual i for attributes x and y.

[5] See Fei, Ranis and Kuo (1978), Shorrocks (1982), and Lerman and Yitzhaki (1985).

[6] See Bourguignon (1979), Cowell (1980), Shorrocks (1980, 1984), Foster and Shorrocks (1988), or Cowell and Jenkins (1995).

[7] An incomplete list of applications of the Shapley value to inequality decomposition includes Sastre and Trannoy (2002), Israeli (2007), Bargain and Callan (2010), Devicienti (2010) and Charpentier and Mussard (2011).

[8] Chantreuil *et al.* (2019) offers a complete methodological note on the Shapley method of decomposition. See the unpublished appendix available from the authors upon request for a short presentation.

Table 4 presents an example with virtual incomes. The first part of the table displays characteristics associated with each of the 8 individuals, the second part presents the income figures associated with equation (1), the third part presents the incomes figures associated with equation (2).

Table 4: Example of income disaggregation by attribute

				Income associated with eq. (1)			Income associated with eq. (2)		
i	w_i	x_i	y_i	$\overline{w}_{x_i}$	$\overline{w}_{x_i,y_i} - \overline{w}_{x_i}$	$w_i - \overline{w}_{x_i,y_i}$	$\overline{w}_{y_i}$	$\overline{w}_{x_i,y_i} - \overline{w}_{y_i}$	$w_i - \overline{w}_{x_i,y_i}$
A	1000	x_1	y_1	1225	-200	-25	1575	-550	-25
B	1050	x_1	y_1	1225	-200	25	1575	-550	25
C	1350	x_1	y_2	1225	200	-75	2250	-825	-75
D	1500	x_1	y_2	1225	200	75	2250	-825	75
E	2200	x_2	y_1	2600	-475	75	1575	550	75
F	2050	x_2	y_1	2600	-475	-75	1575	550	-75
G	2900	x_2	y_2	2600	475	-175	2250	825	-175
H	3250	x_2	y_2	2600	475	175	2250	825	175

This table shows that figures associated with attribute x and with attribute y differ according to the order in which the attribute appears in the income decomposition. The share of income inequality (as defined in what follows by the Gini index) associated with each attribute therefore differ slightly depending on the ordering of attributes, as shown in the following results in Table 5.

Table 5: Relative contributions and Gini index

	Relative contrib. x	Relative contrib. y	Relative contrib. unobserved	Gini index
eq. (1)	60.48%	32.67%	6.85%	0.22
eq. (2)	64.67%	28.48%	6.85%	0.22
mean	62.58%	30.58%	6.85%	0.22

In Table 5 the Gini index is 0.22 and the relative contribution of unobserved attributes to income inequality is 6.85%, *i.e.* 6.85% of the Gini value remains associated with unobserved characteristics. The share of the observed inequality associated with attribute x is 60.48% (resp. 32.67% for attribute y) in the first decomposition and 64.67% (resp. 28.48% for attribute y) in the second decomposition. Because there is no *a priori* reason to choose one decomposition over another, in the following we choose to evaluate the share of the observed inequality associated with each attribute as the mean of the share obtained in each decomposition ordering as shown in Table 5. We empirically discuss the incidence of the ordering of attributes in Section 5.

4 Results: contribution of gender and race to earnings inequality

We now apply the methodology outlined above to US observations, determining the average contribution to earnings inequality of several individual characteristics and their development over time. For each year between 2005 and 2017, and each geographical division, the earnings of each individual are treated as explicable in terms of four attributes capable of generating earnings differences either objectively (*i.e.* based on individual productivity): age (as a proxy for professional experience), education; or discriminatively: gender, race.[9] These four attributes represent 24 (=4!) permutations of the ordering of attributes that we must consider in order to obtain the mean contribution of each attribute to earnings inequality. Overall results are presented in Appendix B. A robustness check using the bootstrap percentile method evaluates the validity of our results in Appendix C.

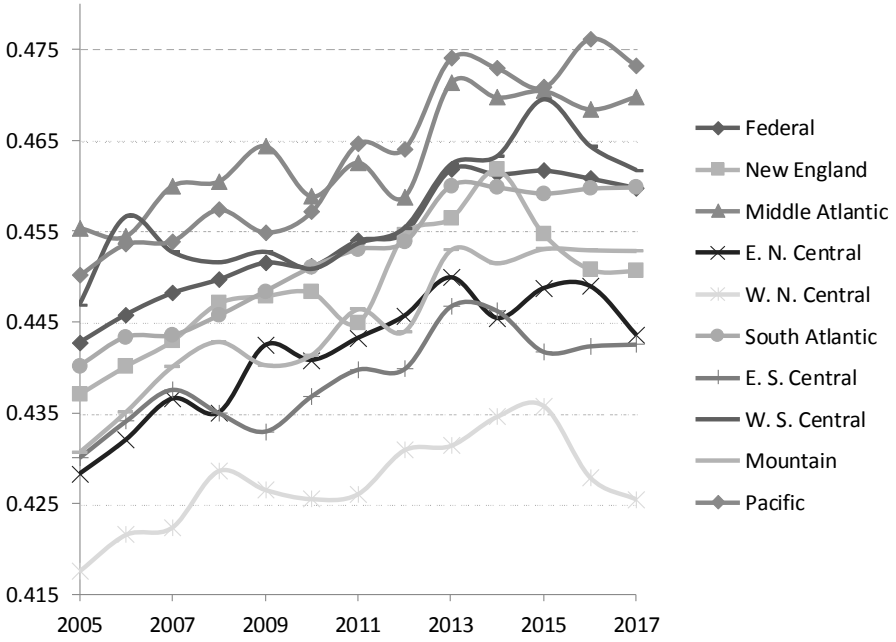
We first concentrated on the evolution of the Gini index. We then analyzed the relative contribution of each of the attributes at the federal level before focusing on race and gender by geographical divisions.

4.1 Change in the Gini index

Table 7 of Appendix B reports the mean contribution of each attribute at the federal level and the geographical division level between 2005 and 2017 as a percentage of the overall earnings inequality observed, as defined by the Gini index. As shown in Figure 2, this total earnings inequality measured by the Gini index varies over the period at the federal level and for each administrative division.

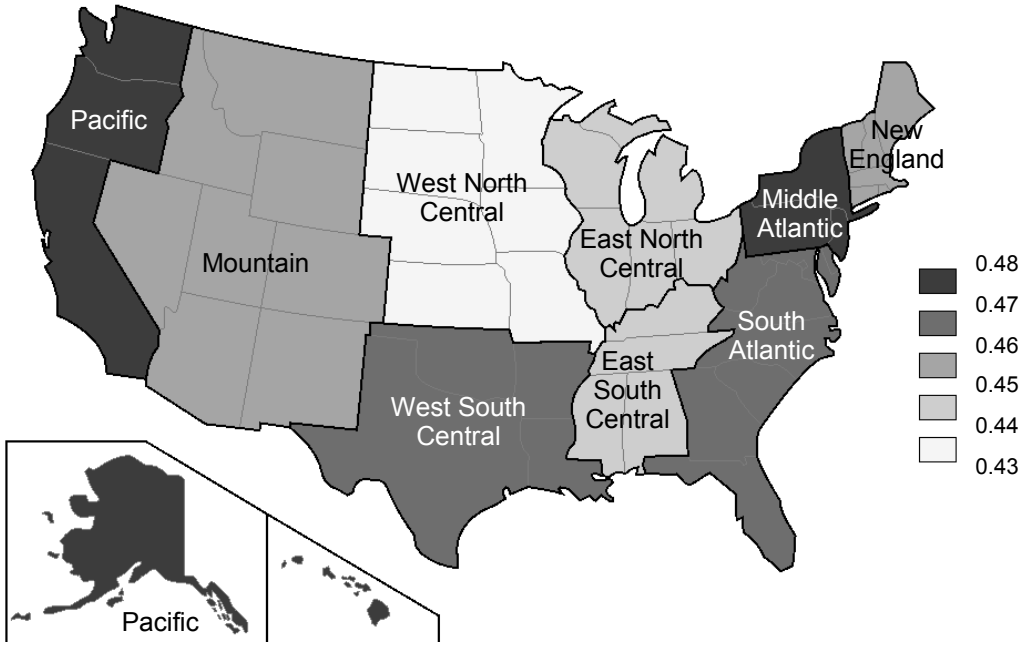
[9]We concede that earnings also depends on occupation. This attribute is excluded from the analysis, however, implying that the impact of occupation on earnings inequality is captured by the residual due to the limited size of each subset of the sample.

Figure 2: Change in the Gini index from 2005 to 2017



The Gini index tended to increase uniformly from 2005 to 2013-2014, irrespective of the division. At the end of the period studied, inequality tended to stabilize at a higher level and was even trending towards a slow reduction. Figure 2 also shows that the relative value of regional earnings inequality is somewhat stable over time. Figure 3 shows the regional map for 2017. It can be noted that seaboard regions (which are among the most populous) are more inegalitarian, since they have a higher Gini index. West, North and East North Central as well as Mountain have the lowest Gini index.

Figure 3: Division map for Gini's index (year 2017)



Not surprisingly, education accounts for most of the earnings inequality among the four selected attributes, with a relative contribution varying from about 15% to 20% of earnings inequality, depending on the year and the geographical division. Then comes gender (about 9% to 14%), age (about 6% to 9%) and finally race (about 1% to 4%). Such a result shows that there are racial and gender discrimination with respect to earnings, but that the inequality observed between Blacks and Whites is mostly linked to non-racial characteristics.

4.2 Relative contributions of each attribute at the Federal level

Figure 4 shows the time variation of each of the four attributes at the federal level. The share of earnings inequality associated with attributes observed is mainly related to education and age, two individual characteristics that legitimately affect earnings since they relate to productivity. Higher certification is indeed associated with higher skills, and greater age with greater experience. By contrast, gender and race are not objective criteria when dealing with productivity. These two characteristics nevertheless account for more than 12% of earnings inequality in a context where total earnings inequality (Gini index) of the Black and White populations taken together is tending to increase.

Figure 4: Change in the average relative contribution of attributes to earnings inequality as a percentage at the Federal level

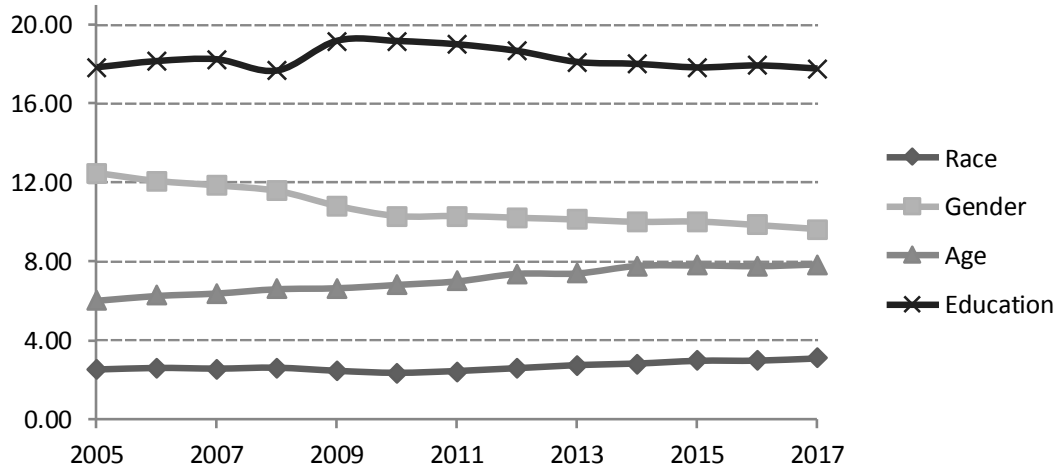


Figure 4 shows that the contribution of education to earnings inequality was approximately the same in 2005 and in 2017 (about 18%), but is not stable over time. The subprime crisis may have induced a significant increase in earnings inequality associated with education, since educated workers were mostly less affected than those with lower educational qualifications. This effect diminished with the economic recovery. By contrast, the contribution of age to earnings inequality tends to increase, except during the three most recent years. Gender earnings inequality falls with the share of inequality associated with gender dropping by 2 to 3 percentage points (from about 12% to about 9%) between 2005 and 2017. From 2010 onward, however, this reduction seems to slow

at the Federal level. Concerning race, its contribution was stable from 2005 to 2008, then fell for two years before consistently increasing up to 2017. It might be supposed that the rise in earnings inequality between Blacks and Whites also originates in the financial and economic crisis. This phenomenon did not reverse during the recovery, however, and even seems to be getting worse.

4.3 Contribution of gender and race by divisions

Let us now concentrate on race and gender. Figures 5 and 6 let us to observe the earnings inequality associated with these two attributes between 2005 and 2017. The Federal trends are confirmed at the administrative division level - an increase in inequality associated with race in the most recent years can be observed in almost all geographical divisions together with a reduction in relative gender inequality over the entire period.

Figure 5: Change in the average relative contribution of race to earnings inequality as a percentage

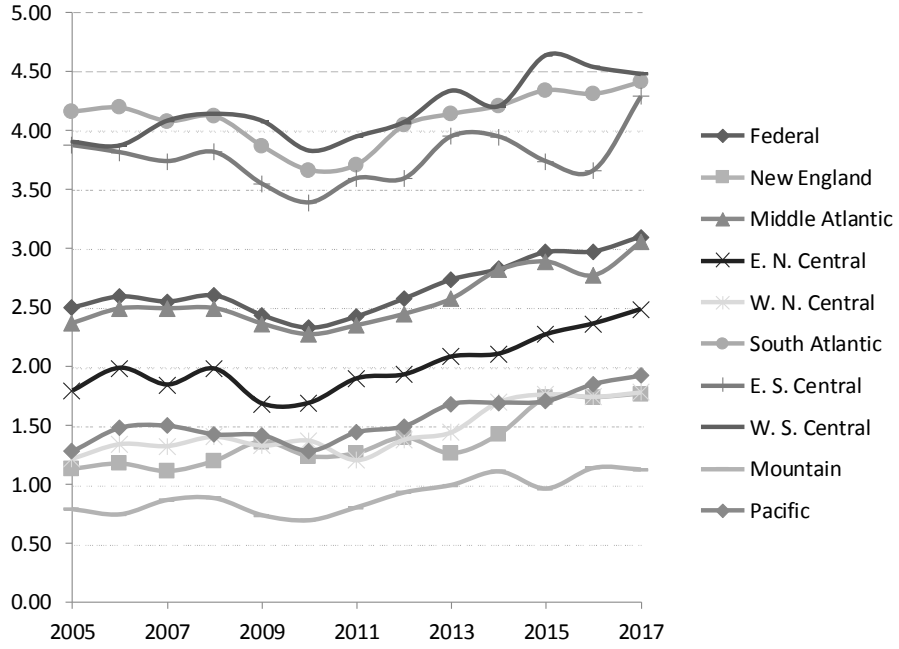
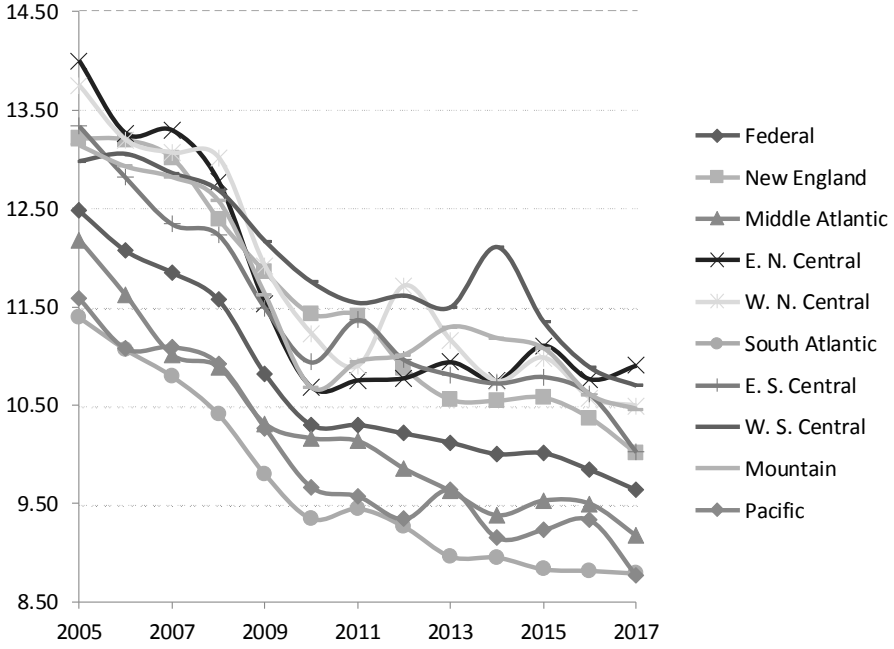


Figure 6: Change in the average relative contribution of gender to earnings inequality as a percentage



Three divisions (West South Central, East South Central and South Atlantic) show a particularly high share of earnings inequality associated with race, rising from about 4% in 2005 to 4.5% in 2017. By contrast, four divisions register a low contribution of race to earnings inequality (in 2017, less than 2% in the Pacific, West North Central and New England divisions), the lowest being Mountain with a contribution of "only" about 1%.[10] For the gender contribution, this fell by at least 2% in every division during the period studied. Middle Atlantic, South Atlantic and Pacific, which correspond to most of the East and West coasts, are the least affected by inequality associated with gender (lower than 10% in 2017). Other divisions display a gender share of from 10.5% to 11.5% in 2017.

Comparing Figure 3 of the Gini index map, the contribution of race (Fig. 7) and that of gender (Fig. 8) highlight some additional points. Coastal divisions, which are the most heavily affected by earnings inequality, are also the least affected by gender inequality. West South Central is the only division which has to deal with both a high level of earnings inequality and a large share of earnings inequality associated with gender. It is also one of the divisions where the contribution of race is high.

[10]Results for the Mountain division are to be treated with caution since this division has a very low share of Blacks in the Black and White population (3.95%, see Table 1). Studying sub-sample sizes shows that the Mountain division has several sub-samples with less than 5 observations per subgroup (accounting for 223 of the 573 observations belonging to a subgroup with fewer than 5 observations), especially in the Black population with least educational qualifications and in those with the highest.

Figure 7: Division map of the contribution of race to earnings inequality (year 2017)

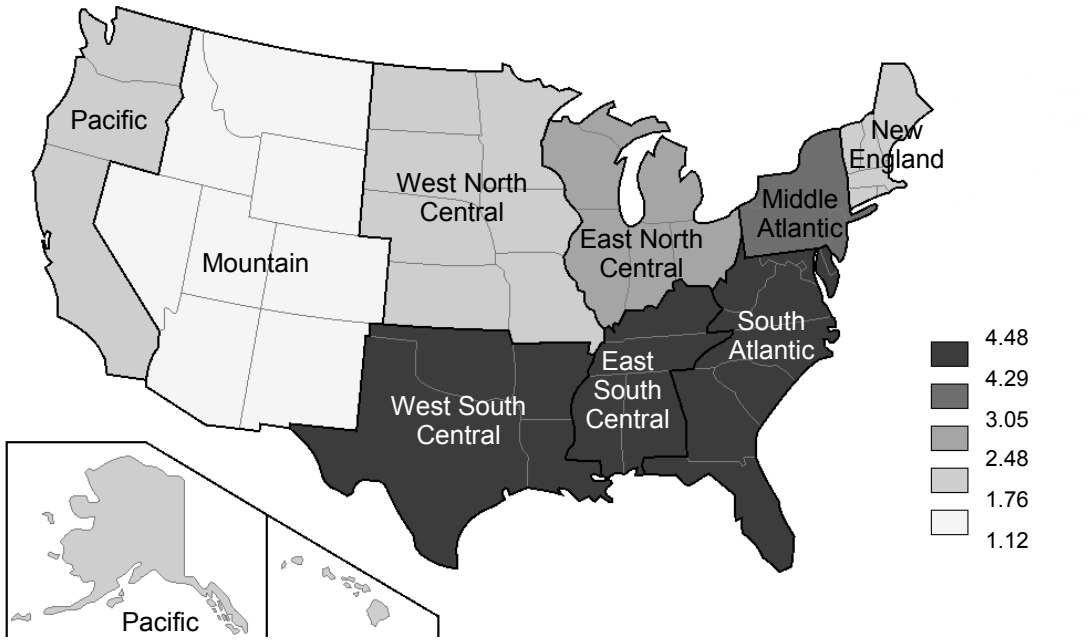
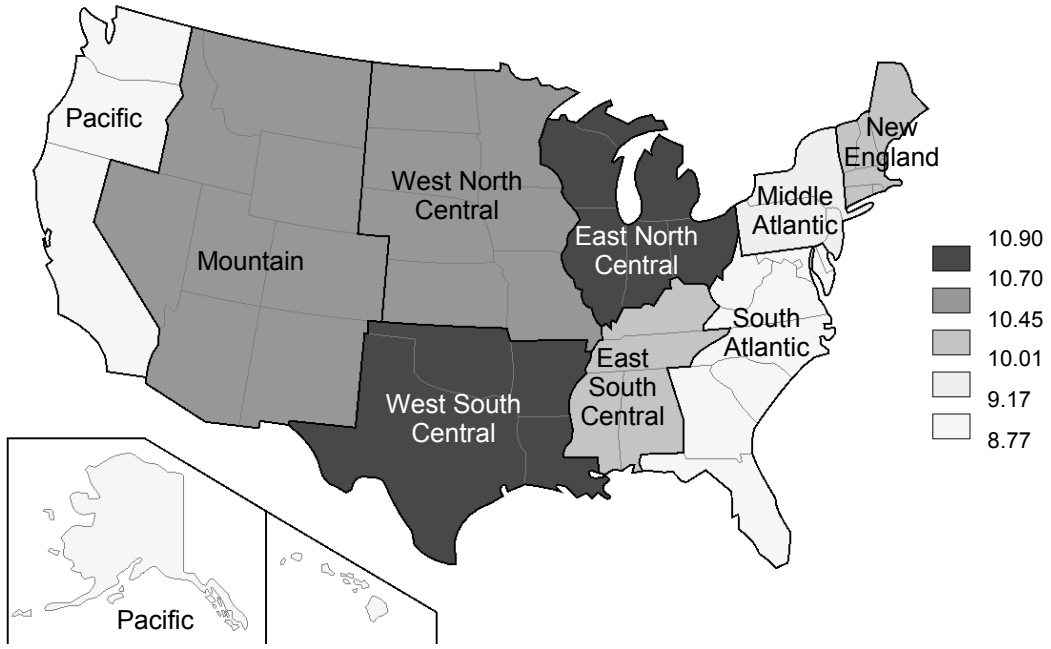


Figure 8: Division map of the contribution of gender to earnings inequality (year 2017)



Now let's take a look at the contributions in values (referred to as absolute contributions) to earnings inequality, which can be used to account for total inequality as measured by the Gini index. The relative contribution is the percentage of the Gini index explained by each of the attributes. The absolute contribution is the "level" of inequality directly explained by each of the attributes. Considering these absolute contributions adds to the analysis since an identical share of the Gini index can be associated with a greater/smaller

inequality value both in space and in time. Figures 9 and 10 display the absolute contribution of race and gender, respectively, with respect to the Gini index, for each US administrative division in 2017 .

Figure 9: Absolute contribution of race (Y axis) with respect to the Gini index (X axis) (year 2017)

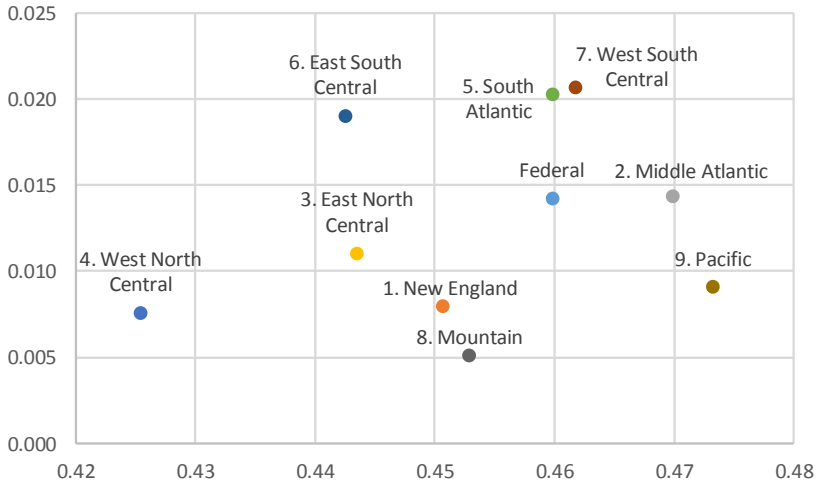
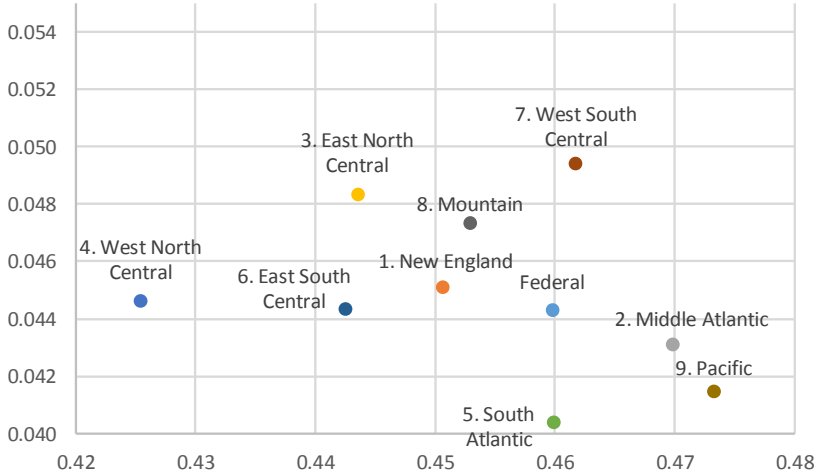


Figure 10: Absolute contribution of gender (Y axis) with respect to the Gini index (X axis) (year 2017)



These two figures highlight specific features of several divisions. West North Central is distinguished by the lowest level of inequality and also by a racial contribution that is among the lowest, with a limited gender contribution. Symmetrically, the figures from the West South Central division show that a high level of inequality tends to go along with a high absolute contribution of both race and gender. Middle Atlantic and Pacific, which display the highest earnings inequality level, do not, however, conform to this trend: the absolute racial contribution to inequality is moderate, and the gender contribution

is among the lowest. Finally, South Atlantic and Mountain both display a moderate level of inequality but with contrasting patterns with regard to the racial and gender contributions. In the South Atlantic division, the absolute contribution of gender is among the lowest and that of race among the highest, while in the Mountain division race has the lowest contribution and gender has a contribution among the highest.

5 Incidence of the ordering of attributes

In order to evaluate the validity of our results, the impact of the ordering of attributes for both race and gender is discussed. We note that the order does not significantly reduce the contribution of one attribute or another.

As mentioned in Section 3, the value associated with an attribute appears in the earnings disaggregation. The first attribute takes the mean value of one of its different modalities, while the following attributes are only successively associated with mean differences. As a consequence, an attribute located in the first position logically captures a higher proportion of earnings than the following attributes. One might think that it also captures more of the total inequality than when it has a lower position, or at the extreme. This is the case that appears in the example presented in Section 3; however the results presented in Table 6 show that this effect is not systemic.

Table 6 presents, on the left-hand side, the racial contribution when race (R) is the first attribute to be considered (then comes education (E), age (A) and gender (G) in that order) and when race is the last attribute to be considered (following education, age and gender, in that order); and on the right-hand side is the gender contribution when gender (G) is the first attribute and when gender is the last attribute.

Table 6: Incidence of attributes' ordering on the relative contribution of race and gender to earnings inequality at the federal level, as a percentage of earnings inequality as defined by the Gini index

	Race		Gender	
	REAG	EAGR	GREA	REAG
2005	2.87	2.11	10.80	13.83
2006	2.98	2.18	10.19	13.58
2007	2.93	2.13	9.90	13.40
2008	2.94	2.20	9.61	13.15
2009	2.83	1.99	8.76	12.46
2010	2.73	1.87	8.29	11.89
2011	2.80	1.98	8.22	11.97
2012	2.94	2.14	8.10	11.94
2013	3.12	2.25	7.99	11.86
2014	3.23	2.32	7.85	11.80
2015	3.37	2.47	7.84	11.83
2016	3.40	2.44	7.62	11.72
2017	3.52	2.55	7.38	11.54

The results in Table 6 confirm some effect of the ordering of attributes on the relative contribution to earnings inequality obtained by the Shapley decomposition method. The impact of race is reduced when considered in the last position as compared with the first position. This reduction (of about 1 percentage point in 2017) does not however challenge our main finding: the earnings spread between blacks and whites has an impact on total inequality that is not insignificant.

Regarding gender, its position in the ordering of attributes also slightly modifies the explained part of total inequality, the magnitude of the impact remaining similar. Notice that the relative contribution of gender is higher when it is placed in the final position. This observation calls into question our previous supposition, that the first position does not automatically correspond to the maximum contribution of an attribute.

Such a result can easily be explained. Earnings associated with the gender attribute is spread over many more modalities when placed in the final position rather than in the first position. In fact, earnings are decomposed into 160 modalities (different age classes, education levels, two races, and two genders) rather than 2 modalities (male/female). If all other attributes are first taken into account, and if the gap between earnings values associated with men and with women is large, the gender contribution to earnings inequality may increase when placed in the final position.

At this stage we observe, for all the orders given in Table 6 and for those resulting from the set of all possible permutations, that race and gender as discriminating factors explain a significant part of overall earnings inequality. Bootstrap testing allows us to confirm the significance of these attributes (see Appendix C).

6 Conclusion

Income inequality decomposition *à la* Shapley enables us to derive the contribution of an individual characteristic to the total earnings inequality observed in the US over the period 2005-2017. An important share of this inequality can be explained by determinants of productivity, *i.e.* the level of skills and the duration of professional experience that we capture through education and age. Other significant factors are less objective. We concentrate on the discriminational part of the inequalities observed, *i.e.* inequalities associated with ethnic concerns or gender issues.

In a context where earnings inequalities increased over the period 2005-2017 at the federal level and for each administrative division, we show that the share of inequality explained by race has also increased. In 2017, we find that the racial contribution to earnings inequality is about 1% to 4% for all of the nine United States Census Bureau designated divisions. Our results confirm those of Huffman and Cohen (2004): the contribution of race to earnings inequalities is much higher in areas densely populated with Blacks. But race is not the most important source of earnings inequality. Gender indeed explains a much higher share of earnings inequality (about 10%) whatever the geographical division. Unlike race, however, inequalities associated with gender were noticeably lower between 2005 and 2017.

There seems to have been a general stability to developments in earnings inequality during the period of study with regard to the contribution of race and gender to this inequality; there is a general stability from one geographical division to another. This means that the relative situation of the divisions persists over time. We identified geographical areas lastingly affected by strong earnings inequalities, with a marked impact of gender and race, such as in West South Central. By contrast, we identified a low level of inequalities, with the weak impact of the two attributes in, for instance, West North Central.

Our analysis does not account for disparities between states. Work at the state level is compromised because of the size of sub-samples. We might expect different results for the states belonging to the South Atlantic division, for instance, which include both former Confederate states (Virginia, North and South Carolina, Georgia and Florida) and Union states (DC, Delaware, Maryland, West Virginia). One way to bypass the sub-sample size issue would be to re-aggregate states according to their economic and historical characteristics. But the choice of factors driving re-aggregation would be open to criticism. Such an issue is left for further research.

Apart from our caution regarding geographical constraints, our results have several public policy consequences. While it does exist, the direct impact of race on earnings remains moderate. This means that the earnings gap between Blacks and Whites finds its origins in characteristics associated with ethnic minorities (low education, poverty, etc.), rather than being a matter of race in itself. In terms of public policy, such results call into question affirmative action in public institutions in general, but would make it more important in education. Our work also highlights the magnitude of gender in earnings inequality, justifying public action in favor of gender equality.

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A United States Census Bureau designated divisions

1. New England
- (ME) Maine
- (NH) New Hampshire
- (VT) Vermont
- (MA) Massachusetts
- (RI) Rhode Island
- (CT) Connecticut

2. Middle Atlantic
- (NY) New York
- (NJ) New Jersey
- (PA) Pennsylvania

3. East North Central
- (OH) Ohio
- (IN) Indiana
- (IL) Illinois
- (MI) Michigan
- (WI) Wisconsin

4. West North Central
- (MN) Minnesota
- (IA) Iowa
- (MO) Missouri
- (ND) North Dakota
- (SD) South Dakota
- (NE) Nebraska
- (KS) Kansas

5. South Atlantic
- (DE) Delaware
- (MD) Maryland
- (DC) District of Columbia
- (VA) Virginia
- (WV) West Virginia
- (NC) North Carolina
- (SC) South Carolina
- (GA) Georgia
- (FL) Florida

6. East South Central
- (KY) Kentucky
- (TN) Tennessee
- (AL) Alabama
- (MS) Mississippi

7. West South Central
- (AR) Arkansas
- (LA) Louisiana
- (OK) Oklahoma
- (TX) Texas

8. Mountain
- (MT) Montana
- (ID) Idaho
- (WY) Wyoming
- (CO) Colorado
- (NM) New Mexico
- (AZ) Arizona
- (UT) Utah
- (NV) Nevada

9. Pacific
- (WA) Washington
- (OR) Oregon
- (CA) California
- (AK) Alaska
- (HI) Hawaii

B Average relative contribution of attributes

Table 7: Average relative contribution of attributes to income inequality as percentage and Gini index

Geog., year	Race	Gender	Age	Education	Unobserved	GINI index
Federal, 2005	2.50	12.47	6.03	17.84	61.16	0.4427
Federal, 2006	2.59	12.07	6.28	18.15	60.91	0.4458
Federal, 2007	2.55	11.85	6.40	18.24	60.97	0.4482
Federal, 2008	2.60	11.57	6.61	17.67	61.55	0.4496
Federal, 2009	2.44	10.82	6.66	19.18	60.92	0.4515
Federal, 2010	2.33	10.30	6.82	19.16	61.38	0.4511
Federal, 2011	2.43	10.30	7.00	18.99	61.28	0.4539
Federal, 2012	2.57	10.21	7.37	18.66	61.18	0.4548
Federal, 2013	2.74	10.12	7.40	18.11	61.64	0.4618
Federal, 2014	2.82	10.00	7.77	18.01	61.40	0.4613
Federal, 2015	2.97	10.01	7.79	17.83	61.39	0.4617
Federal, 2016	2.97	9.84	7.76	17.93	61.50	0.4608
Federal, 2017	3.10	9.64	7.85	17.77	61.65	0.4598
New England, 2005	1.13	13.21	6.09	18.45	61.12	0.4370
New England, 2006	1.18	13.20	6.14	18.30	61.19	0.4401
New England, 2007	1.11	13.01	6.73	18.47	60.68	0.4429
New England, 2008	1.20	12.39	6.92	18.09	61.40	0.4471
New England, 2009	1.36	11.85	7.13	19.56	60.10	0.4479
New England, 2010	1.24	11.42	7.20	19.40	60.74	0.4483
New England, 2011	1.26	11.41	7.37	19.36	60.60	0.4449
New England, 2012	1.40	10.88	7.80	19.23	60.70	0.4546
New England, 2013	1.26	10.55	8.04	18.90	61.24	0.4564
New England, 2014	1.42	10.55	8.50	18.62	60.92	0.4617
New England, 2015	1.73	10.57	8.27	18.44	60.99	0.4547
New England, 2016	1.73	10.37	8.54	18.11	61.25	0.4508
New England, 2017	1.76	10.01	8.43	18.70	61.10	0.4506
Middle Atlantic, 2005	2.37	12.18	5.48	18.92	61.05	0.4553
Middle Atlantic, 2006	2.49	11.62	5.55	19.30	61.04	0.4544
Middle Atlantic, 2007	2.49	11.01	5.62	19.34	61.55	0.4600
Middle Atlantic, 2008	2.49	10.89	6.07	18.52	62.03	0.4605
Middle Atlantic, 2009	2.36	10.31	6.33	19.96	61.04	0.4644
Middle Atlantic, 2010	2.27	10.16	6.15	19.72	61.70	0.4588
Middle Atlantic, 2011	2.35	10.14	6.50	19.42	61.61	0.4625
Middle Atlantic, 2012	2.44	9.85	6.71	19.24	61.75	0.4588
Middle Atlantic, 2013	2.57	9.63	7.13	18.85	61.83	0.4713
Middle Atlantic, 2014	2.81	9.38	7.35	18.59	61.87	0.4697
Middle Atlantic, 2015	2.89	9.53	7.54	18.73	61.31	0.4704
Middle Atlantic, 2016	2.77	9.50	7.48	18.94	61.32	0.4684
Middle Atlantic, 2017	3.05	9.17	7.47	18.39	61.92	0.4698
East North Central, 2005	1.79	14.00	6.18	17.37	60.65	0.4282
East North Central, 2006	1.98	13.26	6.74	17.89	60.13	0.4320
East North Central, 2007	1.84	13.30	6.64	18.42	59.81	0.4365
East North Central, 2008	1.98	12.78	6.60	17.58	61.07	0.4350
East North Central, 2009	1.68	11.53	6.63	19.52	60.64	0.4424
East North Central, 2010	1.69	10.68	6.95	19.60	61.08	0.4408
East North Central, 2011	1.89	10.75	7.39	19.48	60.49	0.4432
East North Central, 2012	1.93	10.78	7.78	18.73	60.79	0.4456
East North Central, 2013	2.08	10.94	7.48	18.53	60.98	0.4499
East North Central, 2014	2.10	10.75	7.84	18.34	60.97	0.4454
East North Central, 2015	2.27	11.10	7.72	18.10	60.80	0.4487
East North Central, 2016	2.36	10.76	7.54	18.26	61.07	0.4489
East North Central, 2017	2.48	10.90	7.72	18.17	60.72	0.4435
West North Central, 2005	1.21	13.75	6.44	16.33	62.27	0.4175
West North Central, 2006	1.34	13.19	6.32	16.88	62.27	0.4215
West North Central, 2007	1.32	13.06	6.66	17.01	61.95	0.4223
West North Central, 2008	1.40	13.02	6.47	16.70	62.42	0.4286
West North Central, 2009	1.33	11.91	7.15	18.01	61.61	0.4265
West North Central, 2010	1.37	11.22	7.12	18.32	61.97	0.4255
West North Central, 2011	1.20	10.90	7.45	17.70	62.75	0.4260
West North Central, 2012	1.38	11.71	7.22	17.44	62.25	0.4308
West North Central, 2013	1.44	11.15	7.51	16.84	63.05	0.4313

West North Central, 2014	1.70	10.74	7.82	16.86	62.89	0.4345
West North Central, 2015	1.76	10.98	7.47	17.27	62.52	0.4357
West North Central, 2016	1.74	10.57	7.55	17.12	63.02	0.4279
West North Central, 2017	1.78	10.49	7.22	17.35	63.16	0.4254
South Atlantic, 2005	4.16	11.39	5.88	18.84	59.74	0.4401
South Atlantic, 2006	4.19	11.06	6.15	18.90	59.70	0.4433
South Atlantic, 2007	4.08	10.79	6.21	19.22	59.71	0.4435
South Atlantic, 2008	4.12	10.41	6.36	18.76	60.36	0.4457
South Atlantic, 2009	3.86	9.79	6.31	20.49	59.54	0.4484
South Atlantic, 2010	3.66	9.35	6.56	20.10	60.33	0.4510
South Atlantic, 2011	3.71	9.45	6.60	20.26	59.99	0.4530
South Atlantic, 2012	4.04	9.26	7.31	19.75	59.64	0.4538
South Atlantic, 2013	4.14	8.96	7.41	19.31	60.18	0.4600
South Atlantic, 2014	4.21	8.95	7.95	19.23	59.66	0.4598
South Atlantic, 2015	4.34	8.83	8.01	18.78	60.04	0.4591
South Atlantic, 2016	4.31	8.82	8.05	18.58	60.25	0.4597
South Atlantic, 2017	4.41	8.79	8.27	18.30	60.23	0.4598
East South Central, 2005	3.87	13.34	7.00	17.10	58.68	0.4300
East South Central, 2006	3.81	12.81	6.90	17.53	58.94	0.4340
East South Central, 2007	3.74	12.34	7.16	17.81	58.95	0.4375
East South Central, 2008	3.81	12.23	7.22	17.22	59.51	0.4350
East South Central, 2009	3.54	11.49	6.97	18.36	59.65	0.4329
East South Central, 2010	3.38	10.94	7.21	18.39	60.09	0.4368
East South Central, 2011	3.59	11.37	7.33	17.87	59.85	0.4397
East South Central, 2012	3.59	10.96	7.44	18.36	59.64	0.4398
East South Central, 2013	3.95	10.81	7.78	17.30	60.16	0.4467
East South Central, 2014	3.95	10.72	7.99	17.10	60.24	0.4462
East South Central, 2015	3.73	10.79	8.23	16.58	60.68	0.4417
East South Central, 2016	3.66	10.61	8.37	16.73	60.63	0.4423
East South Central, 2017	4.29	10.02	8.10	16.99	60.60	0.4425
West South Central, 2005	3.90	12.98	6.24	17.25	59.63	0.4469
West South Central, 2006	3.87	13.05	6.47	17.46	59.16	0.4566
West South Central, 2007	4.08	12.86	6.74	17.14	59.19	0.4527
West South Central, 2008	4.14	12.68	7.26	16.02	59.90	0.4516
West South Central, 2009	4.08	12.16	6.87	17.35	59.53	0.4527
West South Central, 2010	3.83	11.75	7.40	17.44	59.58	0.4508
West South Central, 2011	3.95	11.54	7.20	17.44	59.87	0.4536
West South Central, 2012	4.07	11.61	7.47	16.86	59.99	0.4553
West South Central, 2013	4.33	11.50	7.08	16.27	60.82	0.4623
West South Central, 2014	4.20	12.11	7.35	16.07	60.27	0.4633
West South Central, 2015	4.64	11.35	7.60	16.07	60.35	0.4695
West South Central, 2016	4.53	10.88	7.48	16.53	60.57	0.4644
West South Central, 2017	4.48	10.70	7.63	16.17	61.02	0.4617
Mountain, 2005	0.79	13.14	6.54	14.59	64.94	0.4306
Mountain, 2006	0.75	12.93	6.92	14.39	65.02	0.4351
Mountain, 2007	0.87	12.82	6.68	14.66	64.97	0.4401
Mountain, 2008	0.88	12.58	7.46	14.41	64.67	0.4428
Mountain, 2009	0.74	11.62	7.48	15.97	64.19	0.4403
Mountain, 2010	0.70	10.67	7.47	16.46	64.71	0.4414
Mountain, 2011	0.81	10.94	7.55	15.93	64.78	0.4464
Mountain, 2012	0.93	11.01	7.43	16.20	64.43	0.4440
Mountain, 2013	0.99	11.29	7.76	14.97	64.98	0.4529
Mountain, 2014	1.11	11.18	8.09	15.45	64.17	0.4515
Mountain, 2015	0.96	11.07	8.24	15.35	64.37	0.4531
Mountain, 2016	1.14	10.60	8.41	15.39	64.45	0.4529
Mountain, 2017	1.12	10.45	9.06	14.96	64.40	0.4529
Pacific, 2005	1.28	11.58	6.57	15.91	64.66	0.4501
Pacific, 2006	1.48	11.07	6.92	16.89	63.64	0.4535
Pacific, 2007	1.50	11.09	7.25	16.14	64.02	0.4539
Pacific, 2008	1.42	10.92	7.54	16.06	64.06	0.4574
Pacific, 2009	1.41	10.27	7.53	17.25	63.54	0.4549
Pacific, 2010	1.28	9.66	7.59	17.69	63.78	0.4571
Pacific, 2011	1.44	9.57	7.91	17.71	63.37	0.4646
Pacific, 2012	1.49	9.34	8.78	17.32	63.07	0.4640
Pacific, 2013	1.68	9.64	8.45	16.81	63.42	0.4740

Pacific, 2014	1.69	9.15	8.97	16.72	63.47	0.4729
Pacific, 2015	1.70	9.23	9.06	16.26	63.74	0.4708
Pacific, 2016	1.85	9.33	8.80	16.68	63.35	0.4762
Pacific, 2017	1.92	8.77	8.98	16.44	63.90	0.4732

C Robustness: confidence interval

We performed a robustness check of the results obtained in Section 4 using the bootstrap percentile method. The contributions obtained via the Shapley decomposition method do not *a priori* follow a normal distribution. We therefore performed a bootstrap sampling to calculate a simple percentile confidence interval. For 2017, at the Federal level, we performed 1,000 resamples with replacement of the initial database and, for each sample, calculate the (absolute) contribution as defined in Section 4. Bootstrap Confidence Intervals are reported in Table 8.[11]

Table 8: Absolute contribution and robustness bootstrap test, Federal 2017

	Initial	95% Bootstrap Confidence Intervals			
		lower	mean	upper	std.dev
Race	0.014235	0.014227	0.014237	0.014247	0.000165
Gender	0.044305	0.044297	0.044315	0.044332	0.000276

The 2017 absolute contribution is found to be within 95% of the CI, thus demonstrating the robustness of our results regarding the existence of the two discriminational characteristics (race and gender) when decomposing income inequalities.

[11]Note that bootstrapping in the ACS database requires a large amount of memory and calculation time. Such a calculation would not have been possible without the use of the ATOS BULL Myria computer available at CRIANN, Normandy, France.