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FULL ARTICLE

The welfare effects of occupational segregation by gender and race: Differences across US Regions

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Abstract

Using tools rooted in welfare economics, this paper explores the social welfare loss that arises from occupational segregation by gender and race in the US at the regional level. After controlling for characteristics, the losses are lower in the Northeast than in the South and West according to a wide range of indicators, including those that take into account the relative size of disadvantaged groups (incidence), the magnitude of their losses (intensity), and the inequality among those groups. The West has the highest (conditional) losses, although the intensity of the phenomenon barely differs from that in the South or Midwest.

KEYWORDS
gender, occupational segregation, race, regions, social welfare

JEL CLASSIFICATION
R23; D63; J15; J71

1 | INTRODUCTION

Gender and race/ethnicity are important traits that help explain why individuals hold the jobs they do (Branch, 2007; Reskin & Bielby, 2005). Men of racial minorities and women tend to be concentrated in occupations characterized by lower wages and opportunities (Blau & Winkler, 2018; Del Río & Alonso-Villar, 2015; Kaufman, 2010). However, the mechanism of segregation is complex: members of a group may benefit from one characteristic (e.g., gender) but

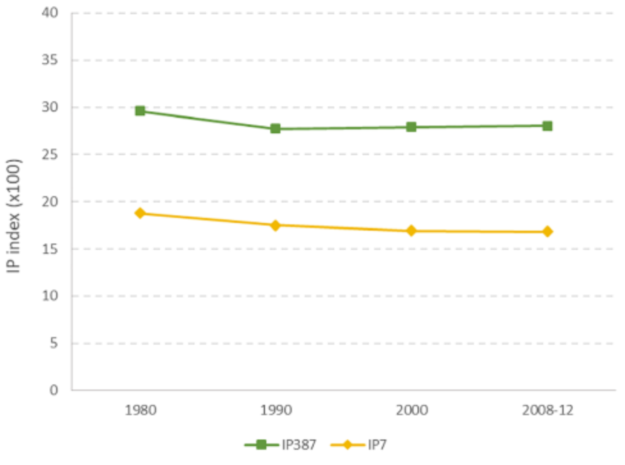


FIGURE 1 Occupational segregation by gender and race with broad and fine occupational classifications (387 and 7 categories, respectively)

be harmed by the other (e.g., race). The intersection of gender and race creates new categories with their own identities (Browne & Misra, 2003; Darity, Hamilton, & Stewart, 2015), a matter that has received little inquiry in the segregation literature, which has been focused mainly on segregation by either gender or race.

To illustrate the magnitude of the phenomenon in the United States, Figure 1 shows the *Ip* segregation index (Silber, 1992), which is a generalization of the dissimilarity index to a multigroup case.[1] By using a detailed occupational classification (387 categories) and 12 gender–race/ethnicity groups, we find that during the period 2008–2012, 28% of workers would have had to change occupations to eliminate gender–race/ethnicity segregation, a percentage quite similar to that observed in 1980 (roughly 30%). When using a broad classification (7 categories) instead, segregation is much lower (17%), which shows the importance of using detailed occupational classifications to capture the phenomenon in its entirety.

Occupational segregation is a mechanism that generates economic inequalities among groups (Blau & Winkler, 2018; Mouw & Kalleberg, 2010) and plays a significant role in explaining the pay gaps of men of racial minorities and women (Blau & Kahn, 2017; Cotter, Hermsen, & Vanneman, 2003; Cunningham & Zalokar, 1992; Kaufman, 2010; Petersen & Morgan, 1995).[2] To the extent that wage inequality among occupations increases over time, occupational segregation perpetuates those inequalities.

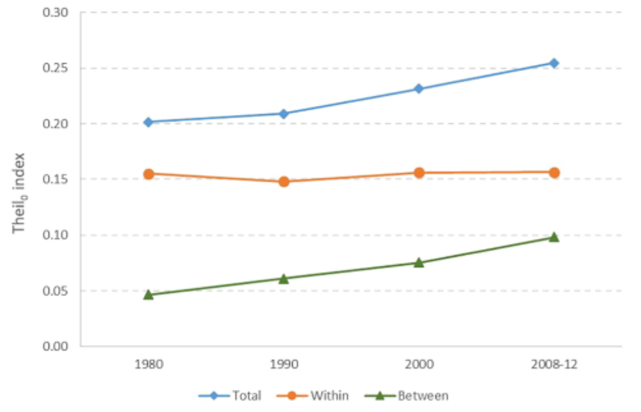
Figure 2 shows the evolution of total wage inequality in the US (measured with the popular Theil_0 inequality index), which is decomposed into two terms: one that shows the wage inequality that exists in the economy due to differences among individuals who work in the same occupation (*within* component) and another that shows the wage inequality that arises from the fact that occupations pay differently (*between* component). The chart reveals that wage disparities within occupations (*within* component) remained stagnant over the last three decades. Wage inequality increased mainly because wage differentials among occupations in 2008–2012 were almost double they were in 1980 (see *between* component).

There is considerable body of literature that explains this between-occupation polarization based on a variety of factors: skill-biased technological change, the growth of low-skill service jobs, changes in the composition of the labour force, increasing globalization and delocalization processes, differences in the institutional mechanisms of social closure by occupations, and differences in returns to education (Acemoglu, 2002; Autor & Dorn, 2013; Mouw & Kalleberg, 2010). However, we know little about how this polarization has impacted the various gender–race groups and the magnitude of the associated aggregated welfare losses.

[1]To build the index we use data from the 1980, 1990, and 2000 censuses and the 2008–2012 five-year sample of the American Community Survey (Ruggles et al., 2010).

[2]In addition, local labour markets with high levels of gender segregation tend to have low female participation rates (Weinstein, 2017). Segregation also results in the devaluation of all work performed by women (Cohen & Huffman, 2003).

FIGURE 2 Total wage inequality decomposed in two terms: inequality within occupations and between them



This literature gap is especially evident at the subnational level because, when accounting for women and men of various races, most scholarship on occupational segregation in the US has been carried out at the national level. However, in different regions, groups may face labour markets that feature different industrial structures, demographic compositions, and education levels—factors that may facilitate or hinder the integration of some groups into the labour market (Patrick, Stephens, & Weinstein, 2016; Reid, Adelman, & Jaret, 2007). Furthermore, cultural and social stereotypes are not homogenous nationwide; whites tend to hold more conservative attitudes toward race and gender in the South than elsewhere (Charles, Guryan, & Pan, 2018; Kuklinski, Cobb, & Gilens, 1997). Significant regional differences also exist in political gender equality indicators, with the Northeast outscoring the Midwest, West, and South (Di Noia, 2002). The incorporation of gender–race groups into the economy and the patterns of labour market segmentation are not independent of the institutional, social, and economic environment surrounding labour markets (Odland & Ellis, 1998; Peck, 1996).

This paper aims to explore the economic consequences of occupational segregation in the US at a regional level by considering 387 occupational categories and using an intersectional framework that distinguishes among 12 gender–race/ethnicity groups. The analysis draws on the 1980, 1990, and 2000 decennial censuses, as well as the 2008–2012 five-year sample of the American Community Survey (ACS), which enables us to explore the evolution of the phenomenon over a 30-year period. We study subnational variation across the four census regions: Northeast, Midwest, South, and West. Although these regions comprise labour markets under different state authorities, they have a long tradition in comparative statistical analyses—because they group states based on historical, demographic, and economic characteristics—and are large enough to account for sizable samples of women and men of six races/ethnicities, which is especially convenient when using detailed occupational classifications. To provide additional insight at a finer geographic scale, we also include evidence of the phenomenon for the 25 states in which the size sample is large enough to differentiate among at least five races/ethnicities.[3]

To measure the consequences of segregation in each region, we use the tools proposed by Alonso-Villar and Del Río (2017a) and Del Río and Alonso-Villar (2015, 2018), which are rooted in the welfare economics and deprivation/poverty literature. This enables us to check whether, when accounting for not only the occupational achievements of the 12 demographic groups but also the occupational inequalities existing within them, the social welfare losses are larger in the South than elsewhere. Another advantage of this approach is that when aggregating the situation of the 12 groups, the losses derived from the concentration of deprived groups in low-paying occupations are not offset by the gains of those groups concentrated in high-paying occupations.

Furthermore, we explore the causes of observed interregional disparities in social welfare losses using the propensity score procedure proposed by DiNardo, Fortin, and Lemieux (1996), as adapted by Gradín (2013) and Gradín, Del Río, and Alonso-Villar (2015). To do this, we build a counterfactual economy in which no regional differences

[3]For the remaining 26 states, we can only distinguish four or fewer racial/ethnic groups.

exist in terms of gender–race composition, education levels, immigration profile, or industrial structure, and check whether regional disparities in welfare losses remain the same.

This paper departs from most studies on segregation in several ways. First, we address segregation using an intersectional framework. Second, we explore spatial disparities in social welfare losses while accounting for detailed demographic groups. Third, we address the economic consequences of segregation using a social welfare function approach, which allows us to account for not only the average occupational achievements of each group (i.e., the average wage of the occupations in which the group works), but also the occupational inequality within the group. Fourth, we account for spatial differences in demographics (gender, race, education, English proficiency, and years of US residence) and industrial structures that may explain those regional disparities. The contribution of each explanatory factor is obtained using the Shapley decomposition, which is independent of the sequence in which the factors are introduced, thus improving the procedures usually employed in the wage gap literature.

Our analysis indicates that regional disparities in social welfare losses associated with segregation by gender and race/ethnicity have increased in the US since 1980. During the period 2008–2012, the monetary losses associated with segregation in the West are estimated at 5.6% of all earnings in the region, whereas such losses in the South, Northeast, and Midwest are 4.9%, 4.5%, and 4.2%, respectively (in 1980, the losses ranged from 5.1% to 5.6%). Around half of these spatial disparities persist after controlling for regional characteristics—racial composition and, to a lesser extent, immigration profile being the most important factors. Conditional welfare losses due to segregation are lower in the Northeast than in the South and West according to a wide range of indicators, including those that account for the relative size of disadvantaged groups (incidence), the magnitude of their losses (intensity), and the inequality among those groups. The West has the highest conditional welfare losses, although the phenomenon's intensity barely differs from that in the Midwest and South.

The paper is structured as follows. Section 2 provides a background on the role that occupational segregation plays in explaining the wage gap. Section 3 introduces the data and methods. Section 4 estimates the welfare losses that each region experienced during the last three decades due to occupational segregation by gender and race/ethnicity. Section 5 tries to explain those regional disparities. Section 6 contains the paper's main conclusions.

2 | BACKGROUND

Notwithstanding the large salary discrepancies that exist between women and men working in the same occupations (Goldin, 2014), segregation plays an important and increasing role in explaining the wage gap. In 2010, occupational segregation accounted for 32% of the gender wage gap, a much larger percentage than in 1980, when it was 11% (Blau & Kahn, 2017). In the case of college graduates, Goldin (2014) found that occupations explain between 30% and 42% of the gender wage gap, depending on the method used. This is a high share, but it is lower than the within-occupation gap.

As is widely documented, gender segregation decreased during the second half of the 20th century,[4] mainly due to the entry of new cohorts of women with higher educational achievements than their predecessors into the workforce (Blau, Brummund, & Liu, 2013) and as a result of political pressure for gender equality that became a force in the 1970s, yet essentially halted just two decades later (Tomaskovic-Devey et al., 2006). Between 1970 and 2015, the percentage of women working in predominantly male occupations (e.g., architects, chemists, dentists, industrial engineers, lawyers) increased considerably, though women still lagged behind in most science, technology, engineering, and mathematics (STEM) fields and men entered formerly female occupations to a much lesser extent (Blau & Winkler, 2018). In 2010, four out of five women (respectively 5 out of 10 men) still worked in occupations with at least 75% of female (respectively male) employment (Hegewisch, Willians, & Henderson, 2011).

[4]The reduction in segregation does not contradict the fact that segregation accounted for a larger share of the gender wage gap in 2010 than in 1980. In line with what was illustrated in Figure 2, although wage disparities within occupations are larger than wage disparities among occupations, the latter increasingly explain wage inequalities.

As with gender, occupational segregation also plays an important role in explaining the black–white wage gap and may account for 20% of that gap (Grodsky & Pager, 2001) or more (Kaufman, 2010). Segregation between blacks and non-blacks decreased in the second half of the 20th century, but segregation between Hispanics and non-Hispanics increased (Queneau, 2009). In any case, race/ethnicity does not affect women and men equally: racial segregation is higher for men than it is for women (Alonso-Villar, Del Río, & Gradín, 2012; Spriggs & Williams, 1996). Furthermore, segregation by gender does not affect all racial/ethnic groups in the same way: it is higher for Hispanics and lower for Asians than it is for other groups (Hegewisch, Liepmann, Hayes, & Hartmann, 2010).

In an intersectional framework in which gender and race/ethnicity are considered jointly, occupations play an important role. Working in feminized occupations and in local labour markets with high levels of gender segregation negatively impacts the wages of white, Hispanic, Asian, and, especially, African American women (Cotter et al., 2003). Among individuals with bachelors' degrees, occupational segregation appears to explain at least half of the wage disadvantage of white, black, and Hispanic women and black men relative to the average wage of high-skilled workers (Del Río & Alonso-Villar, 2015). Roughly half of the wage advantage of white men also comes from their occupational sorting (the occupational advantage is even more intense in the case of Asian men). This indicates that differences in the groups' occupational sorting help to explain intergroup earning differentials.

Scholarship on occupational segregation by gender or race has been mainly undertaken at the national level in the US, although a few studies have reported important spatial disparities (Alonso-Villar & Del Río, 2017b; Gradín et al., 2015; Lorence, 1992). However, these studies did not account for the racial/ethnic diversity of women and men (i.e., they did not distinguish among 6 races/ethnicities), which prevented them from revealing the full extent of labour inequality. This paper aims to address those spatial inequalities using a comprehensive intersectional approach that distinguishes among men and women of various races/ethnicities. To undertake such an analysis using a detailed occupational classification, the study is conducted at a 4-region level to ensure enough observations for all groups in each location, although we provide further information for some states.

3 | DATA AND METHODOLOGY

3.1 | Data

We use the US decennial censuses (covering 1980, 1990, and 2000) and the 2008–12 five-year sample of the American Community Survey—which replaced the census long form after 2000 and reports data on occupation. The dataset, which offers harmonized information, was provided by the Integrated Public Use Microdata Series (IPUMS-USA; Ruggles et al., 2010).[5] The 5-year sample covers 6.9 million workers and includes the two years before and after 2010. The number of workers in the decennial censuses ranges from 5 million in 1980 to 6.4 million in 2000. We distinguish the Northeast, Midwest, South, and West census regions.

With respect to the occupational breakdown, we use the consistent long-term classification provided by IPUMS-USA, which is based on the 1990 Census Bureau classification and accounts for 387 job titles. We use a detailed classification of occupations because otherwise differences among demographic groups within broad categories of occupations would not be captured and so the measurement of segregation, and its economic consequences, would be underestimated (as Figure 1 illustrates). The wage of each occupation is proxied by the average hourly wage, which is estimated based on reported wages and number of hours worked—after trimming the tails of the hourly wage distribution to prevent outliers from skewing the average (for this we eliminate all workers whose wages are either zero, below the 1st percentile or above the 99th percentile of positive values in that occupation).

We consider the 12 mutually exclusive groups of workers that result from combining gender with six racial/ethnic groups: the four major single-race groups not of Hispanic origin (which we label as whites, African

[5]Publicly available at https://usa.ipums.org/usa/. For basic demographics of the groups see the online Appendix.

Americans, Asians, and Native Americans); Hispanics irrespective of race (all labelled as Hispanics); and "other races" (non-Hispanics that self-report some other race or more than one race).[6]

3.2 | Methodology

To quantify a region's social welfare loss, we follow two steps. First, using the index proposed by Alonso-Villar and Del Río (2017a), we quantify the differential between the well-being each gender–race/ethnicity group in that region derives from its occupational sorting and the well-being the group would derive if it were evenly distributed across occupations.[7] We also calculate these losses (gains) in monetary terms using the index developed by Del Río and Alonso-Villar (2015), which has a very intuitive interpretation although it implies disregarding within-group inequalities. These two indices are positive when the group tends to fill highly paid occupations, negative when the opposite holds, and are equal to zero when the group has no segregation or all occupations have the same wage.

Second, we aggregate the well-being losses of the groups (in each region) via the approach developed in Del Río and Alonso-Villar (2018). This method is similar to the one followed in the literature on deprivation and poverty, since a group's well-being loss can be viewed as a shortfall with respect to the case of no segregation.

3.2.1 | Measuring the well-being loss or gain of a group arising from its occupational sorting

To quantify a group's well-being loss or gain that is associated with its occupational sorting, expressed in *per capita* terms, we use index Ψ_1^g (Alonso-Villar & Del Río, 2017a):

$$\Psi_1^g = \sum_j \left(\frac{c_j^g}{C^g} - \frac{t_j}{T} \right) \ln \frac{w_j}{\bar{w}}, \tag{1}$$

where c_j^g denotes the number of workers of group g in occupation j, t_j is the number of workers in that occupation, $C^g = \sum_j c_j^g$ is the size of the group, $T = \sum_j t_j$ is the total number of workers in the economy, w_j is the (average) wage of occupation j, and $\bar{w} = \sum_j t_j w_j / T$ is the average wage of the economy. The ratio $w_j/\bar{w}$ reflects the relative wage of occupation j as compared to the economy's average wage. All these variables refer to the region under study.

To interpret this index, note that Ψ_1^g is positive (respectively negative) when the group is overrepresented (respectively underrepresented) in high-paying occupations and underrepresented (respectively overrepresented) in low-paying ones. This is so because any occupation j in which the group is overrepresented $\left(c_j^g/C^g > t_j/T\right)$ contributes positively to the index if and only if that occupation's wage is higher than the average wage $(w_j/\bar{w} > 1)$.

The value of Ψ_1^g depends not only on the group's earnings but also on the within-group inequality that arises from the fact that some group's members may work in low-paying occupations and others in high-paying ones. This inequality aversion, which diminishes the well-being of groups with larger discrepancies in the occupational achievements of their members, is embodied in the concavity of the *ln* function.

To measure the loss (gain) of a group, we also use the index Γ^g (Del Río & Alonso-Villar, 2015):

[6]The residual "other race" category is not consistent across years. Multiple-race responses have been allowed only since year 2000.

[7]The well-being of a group is measured using a social welfare function commonly used in the literature on income distribution, which implies accounting for the average "income" of the group and also the "income" inequality existing within it.

$$\Gamma^g \equiv \sum_j \left(\frac{c_j^g}{C^g} - \frac{t_j}{T} \right) \frac{w_j}{\bar{w}}, \tag{2}$$

because it has an intuitive meaning: It measures the (*per capita*) monetary loss (or gain) that a group derives from its occupational sorting.

The difference between these two indices is that Ψ_1^g assumes inequality aversion whereas Γ^g does not. Inequality aversion is a convenient property when the group has members with very different occupational achievements, as is the case of Asian women and men.

The approach just described allows us to transcend the mere measurement of unevenness, on which most segregation analyses focus, to address the economic consequences of that unevenness, which is where the main problem lies.

3.2.2 | Measuring welfare losses of the whole society

The above tool is insufficient for determining the welfare loss of an entire region due to segregation. The reason is that some groups may derive gains—while other groups endure losses—stemming from their occupational sorting. One way of dealing with this issue would be to calculate the average well-being losses or gains of the groups involved. However, this approach presumes that advantaged groups' gains offset disadvantaged groups' losses of the same magnitude—an assumption that would be called into question by those people who are inequality averse. A more suitable way of quantifying a region's social welfare loss resulting from the occupational sorting of its demographic groups is to use, as proposed by Del Río and Alonso-Villar (2018), a framework similar to the one employed in the literature on deprivation and poverty.

To obtain the welfare loss of a region due to occupational segregation by gender and race/ethnicity, first, we calculate the well-being loss or gain of each gender–race/ethnicity group g using the index Ψ_1^g (or Γ^g) defined earlier. Then we rank the groups with well-being losses, that is, those with $\Psi_1^g < 0$ ($\Gamma^g < 0$), from high to low levels of loss whereas the groups with no losses, namely, those with $\Psi_1^g \geq 0$ ($\Gamma^g \geq 0$), come next in the ranking, in no particular order. If we denote by $\mathbf{C} \equiv (C^1, \ldots, C^n)$ the vector representing the demographic size of the n gender–race/ethnicity groups and by $p^k = (C^1 + \cdots + C^k)/T$ the share of the first k groups ($k = 1, \ldots, n$), the *social welfare loss curve associated with segregation* (WLAS) at point p^k is defined as the weighted sum of the well-being losses of the first k groups. Namely:

$$W(p^k) = \sum_{g=1}^{k} \frac{C^g}{T} d^g, \tag{3}$$

where d^g is equal to the absolute value of Ψ_1^g (respectively Γ^g) if the group has a well-being (respectively monetary) loss and zero otherwise (at intermediate points p, $W(p)$ is determined by linear interpolation). This curve provides useful information about the social welfare loss of a region (see Figure 3).

The abscissa value at which the curve becomes horizontal, denoted by h, represents the incidence of the phenomenon—namely, the population share that the groups with well-being losses account for. The maximum height of the curve conveys the problem's intensity (i.e., the total cumulative losses of the groups divided by T). Finally, the curvature of the WLAS curve between the origin and point h illustrates the inequality that exits among disadvantaged groups (i.e., those with well-being losses).[8]

[8]The WLAS curves are based on Jenkins and Lambert's (1997) TIP curves, where TIP stands for "the Three I's of Poverty" (incidence, intensity, and inequality). If all disadvantaged groups had the same (*per capita*) losses (i.e., the same value of Ψ_1^g), the WLAS curve would be a straight line between 0 and h. To the extent that some groups have larger losses than others, that part of the curve will no longer be a straight line but will have a curve shape with a higher slope (due to the larger losses of the groups) when closer to 0.

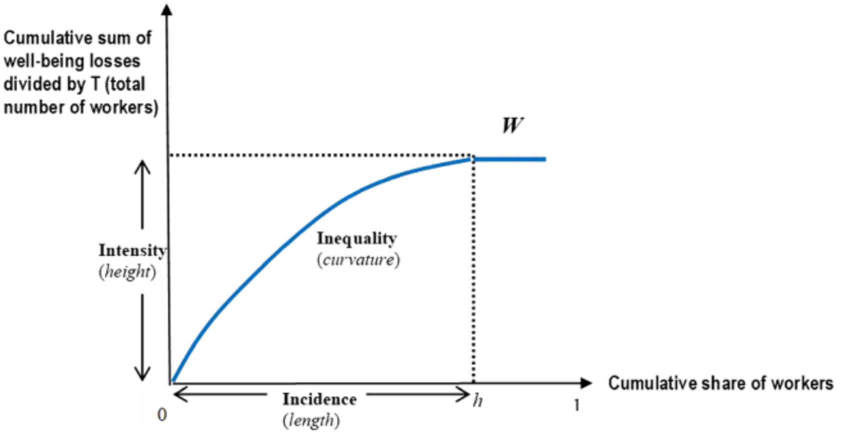


FIGURE 3 The WLAS curve, *W Source*: Del Río and Alonso-Villar (2018)

These curves are a powerful tool because, when one curve dominates another (i.e., when the former is never above the latter and is below it at some point) then we can conclude that the social welfare loss in the first situation is lower than that in the second according to a wide range of indices that satisfy basic properties commonly accepted in the literature on poverty and deprivation.

To measure the social welfare loss, we also use the family of indices proposed by Del Río and Alonso-Villar (2018), which result from adapting the well-known FGT poverty indices to this context:

$$\mathrm{FGT}_{\alpha} = \frac{1}{T}\sum_{s=1}^{S*}(d_s)^{\alpha}, \tag{4}$$

where $\alpha \geq 0$ is an inequality aversion parameter (associated with the welfare loss inequality among groups with losses), d_s is the well-being loss of worker *s* (set equal to the *per capita* well-being loss of the group to which *s* belongs), and s^* is the number of individuals for whom $d_s > 0$.

When $\alpha > 1$, these indices are consistent with the dominance criterion defined by the WLAS curves. It follows that, when a curve dominates another, we can ensure that with any of these indices the social welfare losses would be lower in the economy represented by the former curve. When no domination exists between the two curves (i.e., if the curves cross) the outcome can change depending on which index is used. Note that index FGT_0 (which represents the proportion of individuals belonging to disadvantaged groups, i.e., *h*) and index FGT_1 (which measures the well-being losses of the disadvantaged groups divided by *T*, i.e., the height of *W*) are not consistent with the WLAS dominance criterion. Nevertheless, our empirical analysis employs both the FGT_0 and FGT_1 indices because they allow measuring the incidence and intensity of the phenomenon separately. Our analysis relies also on the FGT_2 index, which combines the three dimensions of the phenomenon—its incidence, intensity, and inequality among deprived groups—at the same time.

4 | SOCIAL WELFARE LOSSES BY US REGION

We begin the analysis by seeing whether there exist significant differences in the regional social welfare losses associated with the occupational sorting of the gender–race/ethnicity groups that work in each of them. After examining the data at the end of our period of analysis (ACS 2008–12, 5-year sample), we will analyse the trends observed since 1980 (based on the decennial censuses).

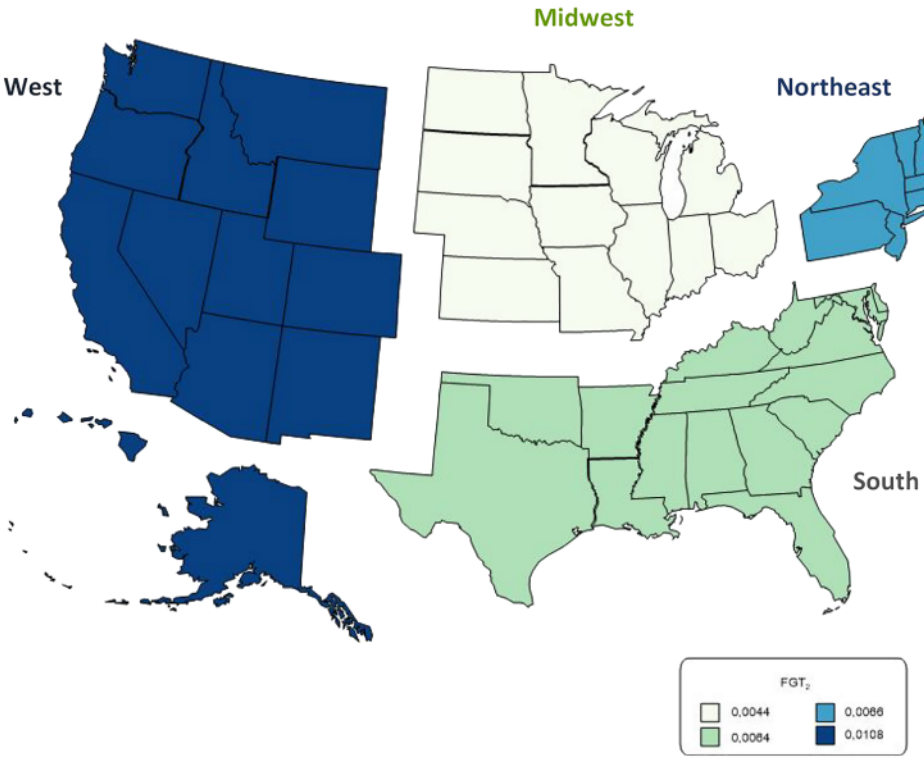


FIGURE 4 Social welfare losses in each region using the FGT_2 index (12 gender–race/ethnicity groups), 2008–12

4.1 | A first look at each region's losses, 2008–2012

To obtain an overview of the problem's intensity, we first calculate the regions' losses in monetary terms (without accounting for within- and between-group inequalities). We find that the West outscores the other regions. Losses in the West represent 5.6% of the region's earnings, which is higher than in the South (4.9%), Northeast (4.5%), and Midwest (4.2%).[9]

How do the regions rank when intra- and inter-group inequalities are also accounted for? Figure 4 (and Table A2 in the Appendix) highlights the welfare losses based on the FGT_2 index, which accounts for not only the intensity of the phenomenon (the average loss per worker), but also its incidence (the percentage of workers who belong to groups with losses) and the inequality among deprived groups.[10] The map shows that the problem is more severe in the West and that the Midwest has the lowest losses in the country.

To shed light on which groups are behind the regions' losses, Figure 5 shows the Ψ_1^g index for each group in each region. With the exception of white women (and men from "other races"), the groups with well-being losses associated with their occupational sorting are the same in all regions. Hispanic women and men have the largest losses, especially in the Northeast and West. African American women and Native American women come next in the ranking, with losses above those of their male counterparts. Like their female peers, African American men fare better in the West whereas Native American men and women have better occupational sorting in the South. White women only experience (small) gains in the West, and their largest losses occur in the Midwest. The occupational achievements of white men are also larger in the West than elsewhere. The analysis indicates that white women and men tend to be better off in places with more racial diversity. This is consistent with previous findings for these two

[9]To obtain these percentages we calculated the FGT_1 index using Γ^g.

[10]From now on, the losses of each group are obtained using Ψ_1^g rather than Γ^g, which implies accounting for occupational disparities within groups.

FIGURE 5 Groups' well-being losses and gains in each region $\left(\Psi_1^g\right)$, 2008–12

groups at the metropolitan level (Alonso-Villar & Del Río, 2017b) and with theories of labour segmentation and queues according to which, when applying to a job, individuals are ranked by their gender and race (Kaufman, 2010; Reskin & Ross, 1990). Asian populations, especially men, seem to fare better in the Midwest and South, regions in which they have a lower presence.[11]

To provide a sense of the spatial discrepancies within regions, Figure 6 shows an estimate of each state's FGT_2 index, accounting for more or fewer races/ethnicities depending on the case (we do not have enough observations for all incumbent female and male groups in all states).[12] We can only distinguish among six races/ethnicities or five (which results from subsuming either Native Americans or Asians within "other races") in 25 states.[13] In the remaining 26 states, which are less racially diverse, we can only account for 2 racial groups (whites and non-whites), 3, or 4. The map also reports the weight each state represents in terms of regional employment.

Western states, especially California (the state with the highest employment by far), Arizona, Colorado, and Washington tend have the largest FGT_2 values in the country. In contrast, the values in Midwestern states are among the lowest (Illinois has the highest value). In the South, Texas stands out as the state with the largest losses, which are lower than those in California. Finally, the losses in the Northeast come mainly from New Jersey and, to a lesser extent, New York.

[11]It is difficult to determine which occupations drive the groups' results in each region since a group's loss or gain depends not only on its degree of over- and underrepresentation in each of the 387 occupations considered in the analysis, but also the relative pay of each. In any case, we find different regional patterns with respect to the occupations in which the groups tend to concentrate. Thus, for example, the overrepresentation of Hispanic men in agriculture is especially intense in the West. The concentration of African American and Hispanic women in health care, education, and child care is much higher in the Northeast than in other regions. The presence of Asian and African American men in managerial and professional occupations is higher in the Midwest and West, respectively, than elsewhere. Other patterns, however, are more uniform nationwide. For example, Hispanic women are highly concentrated in personal services (primarily cleaning), which helps to explain the large losses of this group in the four regions.

[12]The intervals used in the map are based on the Jenks optimization method.

[13]These states are: AZ, CA, CO, WA, and NV (West); FL, GA, MD, NC, OK, TN, TX, and VA (South); IL, IN, MI, MN, MO, OH, and WI (Midwest); and CT, MA, NJ, NY, and PA (Northeast). Full state names are provided in the online appendix.

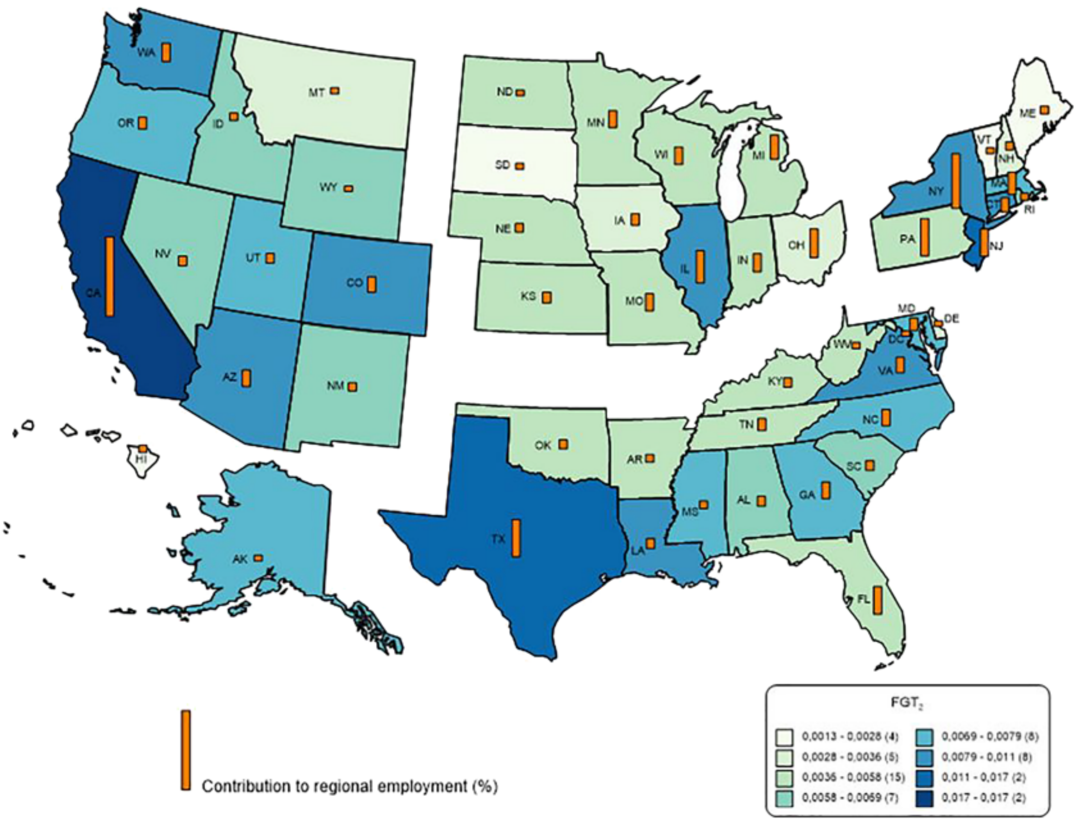


FIGURE 6 Social welfare losses in each state using the FGT_2 index (12 or fewer gender–race/ethnicity groups), 2008–12

4.2 | WLAS curves for each region, 2008–2012

Figure 7 reveals that the WLAS (social welfare loss associated with segregation) curve of the Midwest dominates the others (i.e., it is below than or equal to those of the other regions). This means that the Midwest has the country's lowest social welfare losses not only for the FGT_2 index (as shown earlier) but for a wide range of indices (in particular, all FGT_α indices for which $\alpha > 1$).

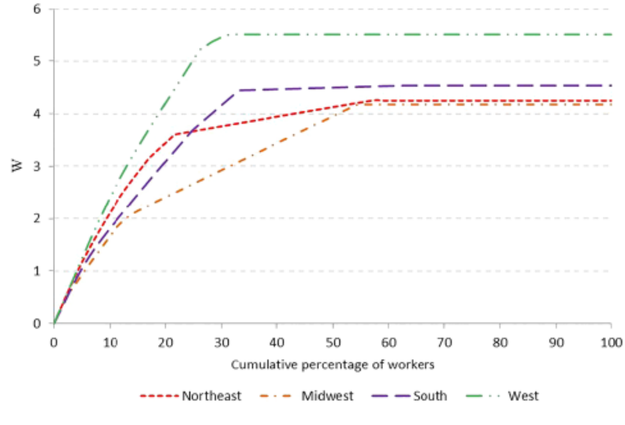


FIGURE 7 The WLAS curve by region, 2008–12

The WLAS curve of the Northeast indicates social welfare losses that are only slightly greater than those in the Midwest, at least in terms of intensity and incidence. Yet the WLAS curve of the Northeast exhibits a much greater curvature than that of the Midwest, which suggests that the difference between these regions are mainly the result of larger discrepancies in well-being losses among deprived groups in the Northeast than in the Midwest.

Figure 7 also shows that the West's WLAS is clearly dominated by that for the other regions, which implies that social welfare losses are the greatest in this region according to many indices. Observe that, in the West, the population share belonging to groups with losses (incidence) is substantially lower than in the other regions (32% vs. more than 50%). The reason of this is that the West is the only region where white women had gains associated with their occupational sorting (Figure 5). The West being dominated occurs because there the phenomenon's intensity far exceeded that in the other regions. Finally, we remark that a ranking between the South and the Northeast is not possible because the curves intersect. In fact, the intensity is clearly higher in the South whereas the FGT_2 index is higher in the Northeast, as shown earlier.

4.3 | WLAS curves for each region, 1980

Figure 8, which plots the WLAS for all regions in 1980, reveals a considerably different scenario. Here, all curves cross, so we are unable to determine which regions are better-off or worse-off. If we ignore all groups except those with the largest well-being losses (which account for 20% of the population), the four regions are virtually indistinguishable. Only when the cumulative percentage of such workers exceeds 20% does the curve of the Midwest start to deviate from those for the other regions, which is indicative of a more severe problem in that region in terms of intensity. The chart also shows that, in 1980, the curves of the other three regions differed little from each other. When expressed in monetary terms, rather than in terms of well-being, the losses in the Midwest represent 5.6% of the regions' wages, whereas the losses in the other regions ranged between 5.1% and 5.3%.

4.4 | FGT indices for each region over the period 1980–2012

Figures 9, 10, and 11 illustrate the evolution of the FGT_2, FGT_0, and FGT_1 indices, respectively. The Midwest, which is less racially diverse than the other regions (see Table A1 in the Appendix), improved its relative position in terms of the FGT_2 index (Figure 9), at least in part, due to the remarkable reduction in the intensity of the phenomenon (Figure 11). Note that white women in the Midwest accounted for a larger (and increasing) share of workers than in the other regions, so how they fared has an important effect on the region's losses. In 1980, the greatest well-being

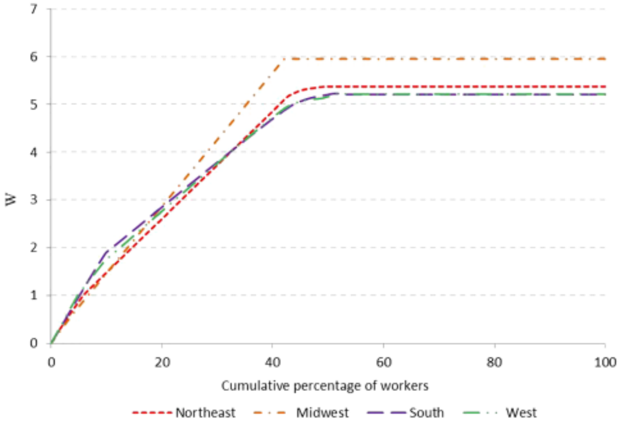
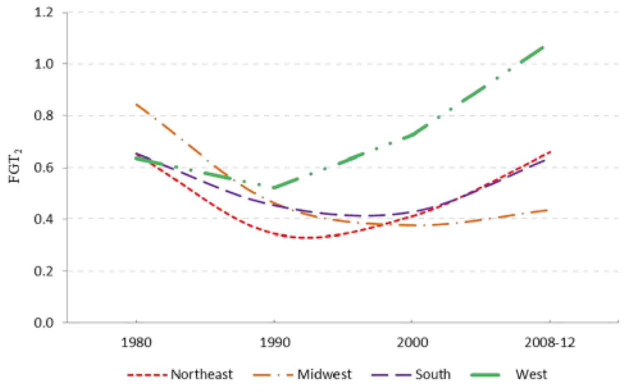


FIGURE 8 The WLAS curve by region, 1980

FIGURE 9 Index FGT_2 (×100) by region



losses for white women did, in fact, occur in the Midwest (see Figures A1–A4 in the Appendix). Although this pattern has remained stable over time, the actual amount of these losses has decreased considerably since 1980. On the other hand, the relatively small group of Asian women experienced notable occupational advances in the period as well. They were experiencing well-being gains (rather than losses) by the 1990s.

However, the experience of male groups in the Midwest does not conform to reductions in the FGT_2 index (Figure A2). African Americans and Hispanics worsened over the period, as they shifted from having small well-being gains in 1980 to experiencing losses soon thereafter. Note that African American and Hispanic men accounted for only 7% of all workers in 2008–2012, which may explain why their worsening situation did not prevent the index from decreasing. The other main racial groups (whites and Asians) had always well-being gains in the period of analysis and, therefore, they have no effect on the FGT_2 index.

In the West, the social welfare losses in terms of the FGT_2 index not only became greater after 1990 (unlike the other regions, where the increase started later) but were also persistently much higher than those of the other regions (Figure 9). Note, however, that the problem in this region over the last decade was not a rise in the incidence of the phenomenon (Figure 10); in fact, the percentage of workers belonging to groups with well-being losses actually declined (those proportions were 59% in 2000 and 32% in 2008–2012). The reason for this is that white (and Asian) women began to experience small well-being gains in the 2000s (Figure A4). The disparities among groups with well-being losses in 2008–2012 cannot help us either to explain why the FGT_2 index is higher in the West than elsewhere.[14] Rather, it was the continuous increase in the initially high share of Hispanic women and men in the West—two disadvantaged groups that experienced greater losses in this period (Figure A4)—that seems to explain

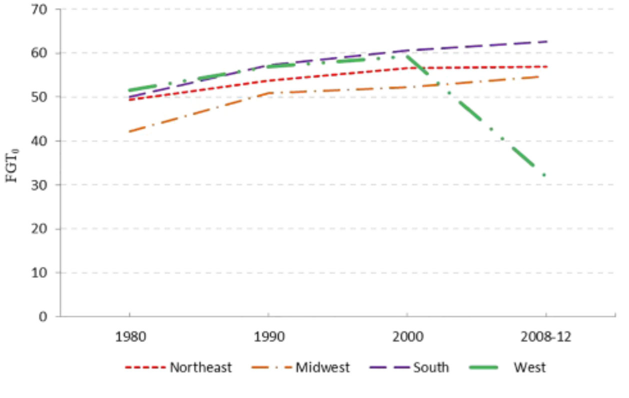


FIGURE 10 Index FGT_0 (×100) by region

[14]As seen in Figure 7, the WLAS curve for this region is almost a straight line in the increasing part of the curve, which implies that the welfare losses of the disadvantaged groups are quite similar. In fact, the coefficient of variation for these losses is 0.36 in the West, as compared with 0.61 in the Midwest, 0.97 in the South, and 1.04 in the Northeast.

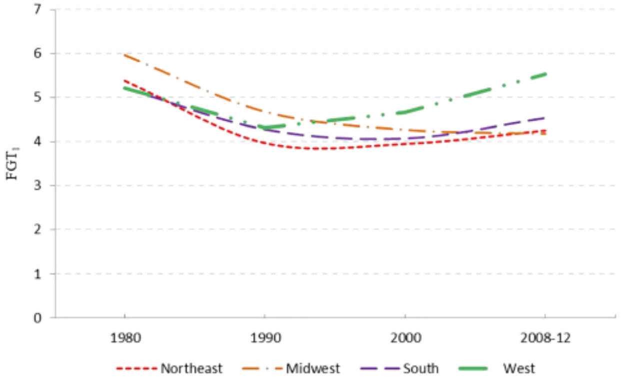


FIGURE 11 Index FGT_1 (×100) by region

the problem's increasing intensity in this region from 1990 onward (Figure 11). This increase appears to have more than offset the positive effect of the evolution of the white and Asian women.

As for the Northeast and South regions, the FGT_2 index evolved similarly in both regions—in that the values were similar at both the beginning and end of the period—but the U-shape is more pronounced in the Northeast because of a sharper fall during the 1980s. This reduction in losses seems to arise from a stronger decrease in the well-being losses of African American women in the Northeast during the first decade (see Figures A1 and A3). This improvement did not last long though: the segregation-related losses suffered by these women had already increased slightly in 2000, and the process continued (with increasing intensity) until the end of the period. In the South, however, African American women had in 1980 greater well-being losses than they did in the Northeast (and also in the other regions) but these losses became less at a fairly steady rate so that, by the end of the period, these women caught up with their counterparts in the Northeast.

5 | CONTROLLING FOR REGIONAL CHARACTERISTICS

The analysis so far has revealed substantial disparities among regions as regards losses in social welfare due to occupational segregation by gender and race/ethnicity. However, these differences could arise not only because some

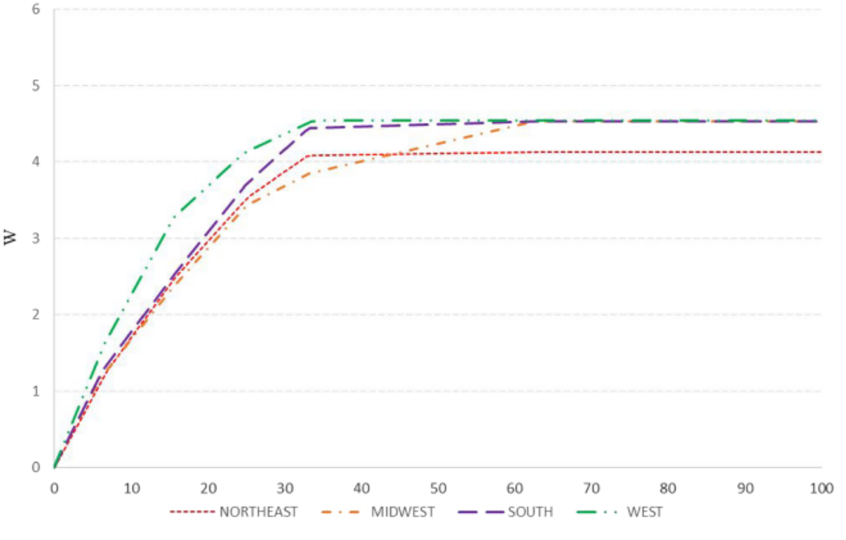
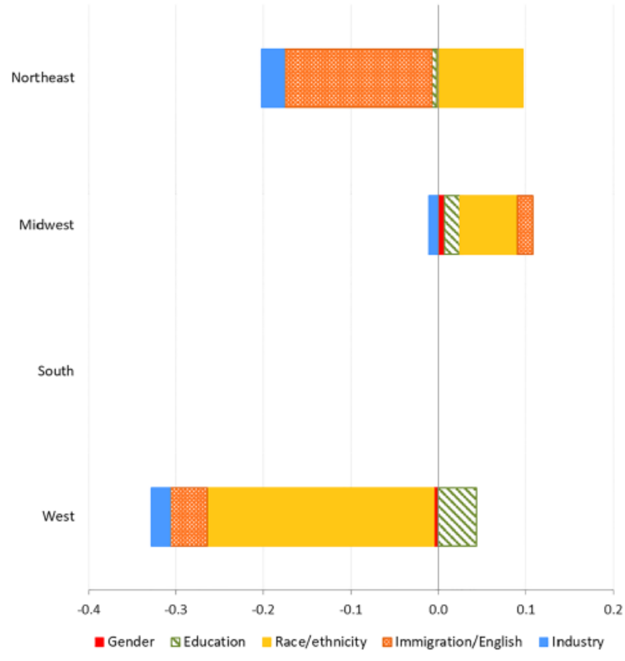


FIGURE 12 The conditional WLAS curves, 2008–12 (reference region: South)

FIGURE 13 Conditional minus unconditional FGT_2 index (×100) (reference region: South)



demographic groups may find it more difficult to secure "good" jobs in some regions than in others but also because of regional differences in such factors as gender–race composition, immigration profile, and education levels, all of which could affect the availability of occupations. These characteristics can be seen as supply-side factors (i.e., what each group brings to the labour market, for example, its educational achievements) and as demand-side factors (those that define the setting in which work occurs; e.g., the educational level of the region).[15] Another demand-side factor, a region's industrial composition, could also affect the occupational sorting of our demographic groups by altering the number of job openings in occupations traditionally associated with a group.

The main question we pose is whether the regional disparities in social welfare losses would remain if there were no differences in the mentioned characteristics. To address this question, we take a "reference region" and then build, for each of the other three regions, a counterfactual economy such that the share of each subgroup defined by the combination of those characteristics is the same in all regions—but with the occupational distribution of each subgroup unchanged from what we observe in the actual data. We refer to the social welfare loss calculated using this counterfactual distribution as the conditional welfare loss. When a region's conditional loss is strongly similar to its unconditional loss, we can surmise that the difference between that region and the reference region does not result from differences in characteristics but rather from differences in the extent to which some gender–race/ethnicity groups are integrated into the labour market. When instead there is a significant difference between the conditional and unconditional loss, regional characteristics account (at least in part) for such regional disparities.

5.1 | Propensity score procedure

We "homogenize" the four regions according to six key characteristics: (i) gender (2 groups); (ii) racial/ethnic composition (5 groups: non-Hispanic whites, African Americans, and Asians, Hispanics of any race, and others)[16]; (iii) years

[15]For a thorough review of the theories behind these factors, see Kaufman (2010).

[16]Because of their small group size, Native Americans were subsumed within the group of individuals from "other" races.

of US residence (3 categories: born in the US, resided there up to 10 years, and resided there for more than 10 years); (iv) English proficiency (4 categories: speaking only English, speaking English very well, well, and not well or not at all); (v) educational achievements (4 levels: less than high school, high school diploma, some college, and bachelor's degree); and (vi) industrial structure (11 sectors, see Table A3). These are the characteristics or attributes to which we refer hereafter.

We use the propensity score procedure, initially proposed in the context of wage discrimination by DiNardo et al. (1996), as adapted by Gradín (2013) to measure occupational segregation and by Gradín et al. (2015) to explore spatial disparities in occupational segregation. Thus, we build a counterfactual distribution for each region so that each "cell" or subgroup resulting from combining the main attributes mentioned above (e.g., Asian immigrant men who have lived up to 10 years in the US, speak English very well, have a university degree, and work in the professional services sector) has the same weight in all regions whereas the occupational sorting of that subgroup is the one we observe in the data. Suppose, for example, that the region of reference is the South. We must reweight the original observations from the other regions by the probability (as predicted by a logit model) that each worker—who has specific attributes—resides in the South rather than that worker's own region. To streamline the presentation, we will explain how to build the counterfactual distribution for a single region: the Midwest.

Let $\mathbf{z} \equiv (z_1, \ldots, z_k)$ denote the vector of the k covariates describing the attributes of each subgroup, and let R be a dummy variable indicating regional membership; thus $R = S$ for workers living in the South and $R = M$ for those living in the Midwest. The weighting scheme,Φ_z, by which we give the Midwest the same characteristics as the South can be estimated from the data as follows:

$$\Phi_z = \frac{\frac{\Pr(R=S|\mathbf{z})}{\Pr(R=S)}}{\frac{\Pr(R=M|\mathbf{z})}{\Pr(R=M)}} = \frac{\Pr(R=M)}{\Pr(R=S)}\frac{\Pr(R=S|\mathbf{z})}{\Pr(R=M|\mathbf{z})}.$$

The first term can be approximated by the ratio of the Midwest's population to the South's population samples. The second term can be obtained by estimating the probability of an individual with attributes $\mathbf{z}$ residing in the South (rather than the Midwest). For that estimation, we use a logit model over the pooled sample of observations from both regions:

$$\Pr(R=S|\mathbf{z}) = \frac{\exp\left(\mathbf{z}\hat{\boldsymbol{\beta}}\right)}{1+\exp\left(\mathbf{z}\hat{\boldsymbol{\beta}}\right)},$$

where $\hat{\boldsymbol{\beta}}$ is the associated vector of estimated coefficients.

We employ this procedure to construct a counterfactual economy in the Midwest. The difference between a conditional index for the Midwest and the unconditional one gives us a measure of the difference in social welfare loss between the Midwest and the South that is explained by our vector z of covariates. Following Gradín (2013), this explained part can be further disaggregated into the respective contributions of each factor (which can be either a single covariate or a set of covariates) via the Shapley decomposition—a technique commonly used in the literature on income distribution but less known in the wage gap literature.[17]

[17]For example, to obtain the contribution of race/ethnicity, we calculate the prediction of Pr($R = S|\mathbf{z}$) by assuming that all coefficients except for those of race/ethnicity dummies are zero; then we compare the loss in the Midwest resulting from this counterfactual distribution to the loss with the actual distribution. Next, we calculate the prediction while assuming zero coefficients for all covariates except for race/ethnicity and one other covariate (e.g., years of US residence). The resulting counterfactual is compared to the counterfactual where only the variable years of US residence is taken into account. The analysis is repeated but with education as the other covariate accounted for, and so on. This informs us about the marginal contribution of race/ethnicity when this is the second factor we control for. We continue by following the same procedure while considering all possible sequences where race/ethnicity is the third factor to change and so on. Finally, we average over all possible marginal contributions of race/ethnicity.

Our conditional analysis yields the welfare loss that the Midwest would have had if it did not differ from the South with regard to gender and racial/ethnic composition, years of residence, English proficiency, educational achievements, and industrial structure. The same procedure is then followed for the West and Northeast regions.

5.2 | Are there regional differences in conditional welfare losses?

Figure 12, which displays each region's conditional WLAS curves in 2008–12 (with the South as the reference region), reveals that the picture changes substantially as compared with the unconditional analysis (Figure 7).[18]

First, although the West's curve is still dominated by the others, the intensity of that region's welfare loss no longer differs much from that in those other regions. Second, the Midwest's WLAS curve no longer dominates all others, and its maximum height (which embodies the intensity of the phenomenon) is no longer the lowest. Third, although controlling for characteristics reduces by half the interregional disparities in welfare losses,[19] the conditional analysis shows that notable differences among regions persist. More specifically, the phenomenon clearly reaches its lowest intensity in the Northeast. Also, the Northeast's WLAS curve dominates those for the South and West. Thus we conclude that, for a wide range of indices, the social welfare losses are lower in the Northeast than in the South and West once we control for characteristics.[20] In particular, the values of the FGT_2 index are 0.55 for the Northeast, 0.64 for the South, and 0.8 for the West (0.53 for the Midwest).

The question that now arises is: Which of the characteristics we consider in the conditional analysis are the most explanatory of the actual regional disparities? To answer that question, we use the FGT_2 index and decompose the change between each region's conditional and unconditional welfare loss into the contribution of each factor: gender composition, racial/ethnic composition, immigration profile (which combines the variables of years of US residence and English proficiency), educational achievements, and industrial structure. Figure 13 reports the contribution of these factors—determined via Shapley decomposition—for each region.

We start by explaining how to interpret this chart. First of all, the South is our reference region and so there is no difference there between the conditional and unconditional welfare loss. Second, with reference to the figure's horizontal axis, the positive factors (respectively negative) are those that would cause the FGT_2 index to increase (respectively decrease). So, for example, if workers in the West region had the same education attainments as those in the South, then the index would be higher than when calculated using the actual (i.e., not the counterfactual) distribution. Yet, if the West were characterized by the same gender and racial/ethnic composition, immigration profile, and industrial structure as the South, then the index would be lower than is actually the case.

The figure clearly shows that, in the West, the net effect of all our factors taken together is both negative and large. Therefore, if this region had the same attributes as the South, then, according to the FGT_2 index, its welfare loss would be lower than what we actually observe. This result is consistent with the West's WLAS curve being much closer to the other regions' curves in Figure 12 than it is in Figure 7.

We infer from Figure 13 that racial/ethnic composition and the immigration profile are key drivers of regional disparities in social welfare losses; education achievements and industrial structure play lesser roles.[21] The analysis suggests that a large part of the high unconditional welfare losses in the West comes from its racial/ethnic composition. On the contrary, the lower losses in the Midwest arise mainly from its lower racial diversity. Notwithstanding, regional disparities still persist after these characteristics have been taken into account. The Midwest and Northeast have lower welfare losses associated with occupational segregation by gender and race/ethnicity than the South and West.

[18]The coefficients of the logit regressions are shown in Table A3.

[19]Using the coefficient of variation, regional disparities in terms of FGT_2 decline by 50%.

[20]All of the above results are robust to changing the reference region.

[21]These outcomes are unaffected by our choice of the reference region.

6 | FINAL COMMENTS

Between 1980 and 2012, the proportion of white men in the US decreased from 48% of total employment to 35%. The country's high and increasing diversity in terms of race and immigration and the increasing incorporation of women into the labour market pose important challenges. Addressing gender–race inequalities in the labour market is a key issue because this setting establishes individuals' economic positions and the perceptions of members of various social groups regarding their opportunities.

By distinguishing among 12 gender–race/ethnicity groups and nearly 400 occupational titles, this paper has quantified the segregation-related losses of each census region, accounting for each group's well-being loss in a manner consistent with the poverty/deprivation literature. Our findings indicate that the phenomenon is not homogenous across the country and that regional disparities have increased over time. In 1980, the Midwest exhibited the greatest losses (representing 5.6% of this region's earnings), surpassing those of the South, Northeast, and West (which ranged from 5.1% to 5.3%). Three decades later, the Midwest had the lowest losses (4.2%), whereas the West's losses (5.6%) exceeded by far those of the other regions (between 4.5% and 4.9%), a pattern that began in 1990.

The reduction in the Midwest's losses appears to be explained by the occupational advancements of white women—who account for an important and increasing share of workers and who were in a worse situation there in 1980 than in other regions—and Asian women. In the West, the occupational achievements of Hispanic women and men, who account for a large share of workers, deviated more dramatically (and increasingly) from those of their African American counterparts (who are less concentrated in low-wage occupations in this region than in the others). The worsening of Hispanics in the West, which is a growing population, seems to explain why social welfare losses increased there over time (despite the occupational advancements of African American women).

After controlling for regional characteristics—racial composition and, to a lesser extent, immigration profile being the most important factors—we found that at least half of the interregional differences in social welfare losses disappear, although some spatial disparities persist. The conditional losses associated with occupational segregation by gender and race/ethnicity are lower in the Northeast than in the South and West in terms of incidence (share of deprived groups), intensity (average loss per worker), and inequality among deprived groups. The intensity of the phenomenon is also lower in the Northeast than in the Midwest. The West has the highest conditional losses, although the average loss per worker in that region barely differs from that in the South or Midwest.

The analysis suggests that the integration of women and racial/ethnic minorities into the labour market differs across regions beyond spatial disparities in groups' attributes and industrial structures; hence there may well exist other factors associated with the characteristics of the regions—such as citizens' attitudes toward gender and race, government policies, and social capital—that help to explain these differences. The role played by these other factors is beyond the scope of this paper, but our findings offer fruitful avenues for further research on this topic.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of this article.

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APPENDIX A

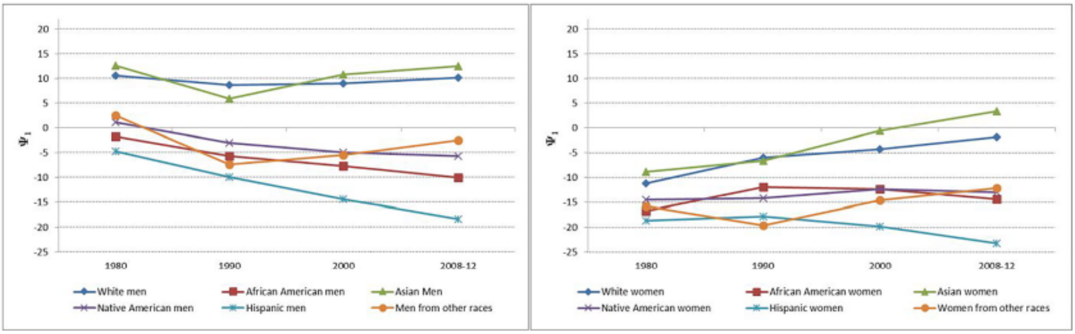

FIGURE A1 Well-being losses (gains) of the gender–race/ethnicity groups, Northeast

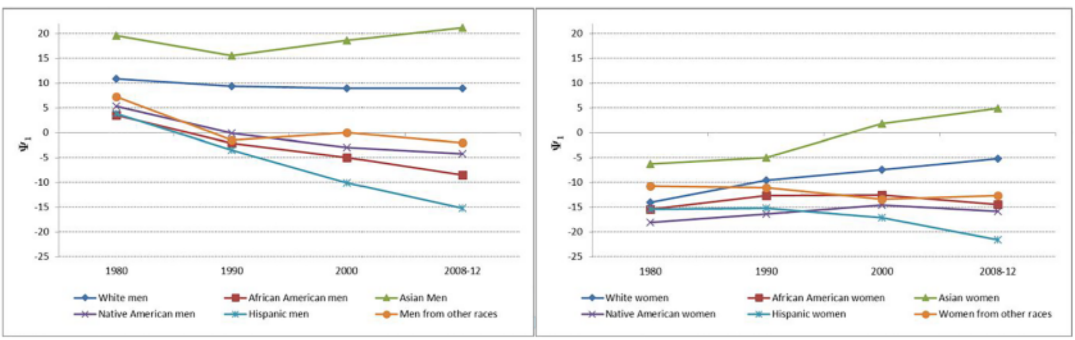

FIGURE A2 Well-being losses (gains) of the gender–race/ethnicity groups, Midwest

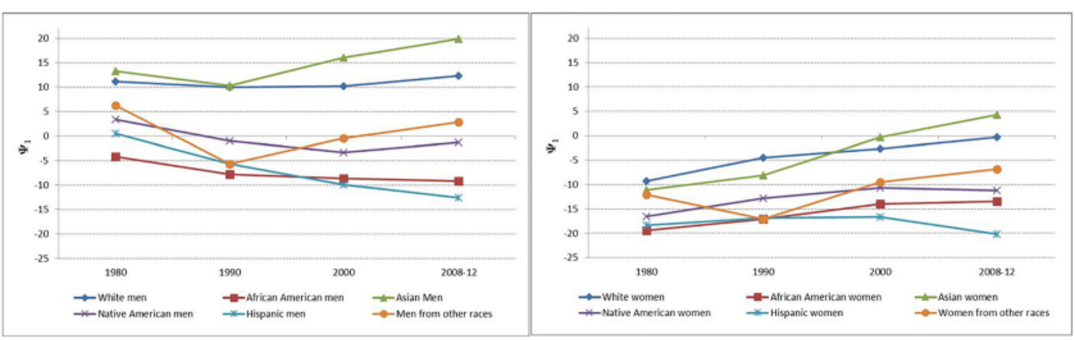

FIGURE A3 Well-being losses (gains) of the gender–race/ethnicity groups, South

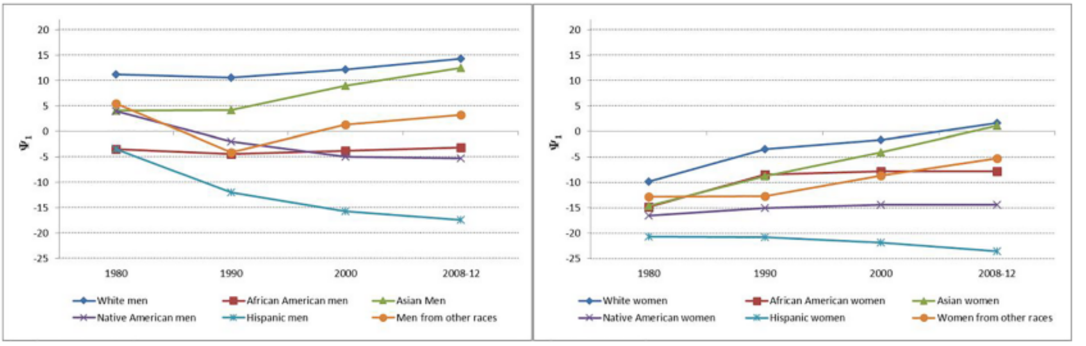

FIGURE A4 Well-being losses (gains) of the gender–race/ethnicity groups, West

TABLE A1 Demographic weights of gender–race/ethnicity groups (%)

	1980					1990					2000					2008–12				
Gender-race/ethnicity groups	US	Northeast	Midwest	South	West	US	Northeast	Midwest	South	West	US	Northeast	Midwest	South	West	US	Northeast	Midwest	South	West
White men	48.3	49.8	52.5	46.0	45.0	43.5	44.7	48.5	42.0	39.2	39.8	41.2	45.3	38.2	34.9	35.5	37.3	42.5	33.4	30.3
African American men	4.9	3.9	3.5	8.1	2.5	4.7	4.1	3.3	7.6	2.3	4.6	3.9	3.4	7.4	2.0	4.8	4.2	3.4	7.7	2.0
Asian Men	0.9	0.7	0.4	0.3	2.7	1.5	1.4	0.7	0.7	3.9	2.0	2.2	1.0	1.1	4.3	2.7	3.1	1.4	1.7	5.3
Native American men	0.3	0.1	0.2	0.3	0.6	0.3	0.1	0.2	0.3	0.6	0.3	0.1	0.2	0.0	0.6	0.3	0.1	0.2	0.2	0.5
Hispanic men	3.4	2.4	1.1	3.3	7.6	4.6	3.4	1.5	4.2	10	6.0	4.2	2.4	6.0	11.5	8.5	6.2	3.6	8.9	14.6
Men from other races	0.1	0.1	0.0	0.1	0.1	0.0	0.1	0.0	0.0	0.1	0.9	0.9	0.6	0.7	1.4	0.8	0.7	0.6	0.7	1.2
White women	34.3	36.6	37.6	31.7	31.7	35.4	37.7	40.3	33.3	31.1	34.0	36.5	39.9	31.7	29.2	31.7	34.6	39.2	29.1	26.1
African American women	4.7	4.0	3.5	7.6	2.1	5.1	4.7	3.8	8.1	2.1	5.3	4.8	4.1	8.6	2.0	5.8	5.2	4.4	9.4	2.0
Asian women	0.8	0.5	0.3	0.3	2.4	1.3	1.1	0.5	0.6	3.5	1.8	1.8	0.8	1.0	4.0	2.5	2.7	1.2	1.5	5.2
Native American women	0.2	0.1	0.1	0.2	0.5	0.3	0.1	0.2	0.3	0.6	0.3	0.1	0.2	0.3	0.6	0.3	0.1	0.2	0.2	0.5
Hispanic women	2.2	1.7	0.7	2.1	4.8	3.1	2.5	1.0	2.9	6.5	4.2	3.5	1.6	4.1	8.1	6.4	5.1	2.5	6.3	11.0
Women from other races	0.0	0.0	0.0	0.0	0.1	0.0	0.1	0.0	0.0	0.1	0.7	0.8	0.5	0.6	1.2	0.8	0.7	0.6	0.7	1.2

TABLE A2 Social welfare losses indices (× 100) by region (using Ψ_1^g)

Northeast	FGT_0	FGT_1	FGT_2
1980	49.36	5.38	0.65
1990	53.84	3.97	0.34
2000	56.59	3.95	0.41
2008–2012	56.91	4.25	0.66
Midwest	FGT_0	FGT_1	FGT_2
1980	42.27	5.96	0.84
1990	50.89	4.67	0.46
2000	52.32	4.26	0.38
2008–2012	54.76	4.17	0.44
South	FGT_0	FGT_1	FGT_2
1980	50.04	5.21	0.65
1990	57.32	4.28	0.45
2000	60.66	4.07	0.43
2008–2012	62.69	4.53	0.64
West	FGT_0	FGT_1	FGT_2
1980	51.54	5.21	0.64
1990	56.88	4.32	0.52
2000	59.31	4.67	0.72
2008–2012	31.84	5.52	1.08

TABLE A3 Logit regressions for the probability of working in the South (pool samples of the South and other region): estimated coefficients (standard errors below)

	Northeast	Midwest	West
Gender:			
Male	--	--	--
Female	0.017 (0.003)	−0.045 (0.003)	0.043 (0.003)
Education:			
Less than High School	--	--	--
High School	−0.249 (0.006)	−0.084 (0.006)	0.007 (0.005)
Some College	−0.104 (0.006)	−0.134 (0.006)	−0.316 (0.005)
Bachelor's Degree	−0.314 (0.006)	−0.025 (0.006)	−0.266 (0.005)
Race/ethnicity:			
White	--	--	--
Black	0.788 (0.005)	1.041 (0.005)	1.339 (0.006)
Asian	0.257 (0.008)	0.256 (0.010)	−1.229 (0.007)
Hispanic (any race)	0.900 (0.007)	1.044 (0.007)	−0.641 (0.005)
Other	0.427 (0.011)	0.367 (0.011)	−0.723 (0.008)
Years of residence:			
Born in the US	--	--	--
Immigrant <=10 years	−0.426 (0.008)	0.204 (0.010)	0.349 (0.008)

TABLE A3 (Continued)

	Northeast	Midwest	West
Immigrant >10 years	−0.557 (0.006)	0.233 (0.007)	−0.101 (0.005)
English:			
Only English	--	--	--
Very well	−0.307 (0.006)	0.083 (0.007)	−0.037 (0.005)
Well	−0.371 (0.009)	−0.117 (0.011)	−0.111 (0.008)
Not well or not at all	−0.374 (0.010)	−0.083 (0.012)	−0.224 (0.009)
Industry:			
Agriculture, forestry, fisheries, and mining	--	--	--
Construction	−0.438 (0.012)	0.127 (0.009)	0.250 (0.009)
Manufacturing-1	−0.626 (0.012)	−0.650 (0.009)	0.076 (0.009)
Manufacturing-2	−0.675 (0.012)	−0.392 (0.009)	0.303 (0.009)
Transportation, communications, other public utilities and wholesale trade	−0.645 (0.011)	−0.050 (0.009)	0.104 (0.008)
Retail trade	−0.628 (0.011)	−0.078 (0.008)	0.139 (0.008)
Finance, insurance, and real estate	−0.844 (0.011)	−0.092 (0.009)	0.125 (0.009)
Business and repair services	−0.589 (0.012)	0.002 (0.010)	0.058 (0.009)
Personal services, and entertainment and recreation services	−0.665 (0.012)	0.002 (0.010)	−0.159 (0.009)
Professional and related services	−0.808 (0.011)	−0.107 (0.008)	0.115 (0.008)
Public administration and active duty military	−0.333 (0.012)	0.399 (0.010)	0.147 (0.009)
Intercept	1.446 (0.011)	0.404 (0.009)	0.630 (0.008)
Number of observations	3,796,796	4,071,446	4,070,021
Pseudo-R2	0.030	0.043	0.063
Wald chi2(23)	81,059.1	111,381.2	168,385.8

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Resumen. Este artículo utiliza herramientas arraigadas en la economía del bienestar para estudiar la pérdida de bienestar social que surge de la segregación ocupacional por género y raza en los Estados Unidos a nivel regional. Después de controlar las características, las pérdidas son menores en el Nordeste que en el Sur y el Oeste, de acuerdo con una amplia gama de indicadores, incluidos los que tienen en cuenta el tamaño relativo de los grupos desfavorecidos (incidencia), la magnitud de sus pérdidas (intensidad) y la desigualdad entre grupos. El Oeste tiene las pérdidas más altas (condicionales), aunque la intensidad del fenómeno apenas difiere de la del Sur o la del Medio Oeste.

抄録: 本稿では、福祉経済学に根付くツールを用いて、地域レベルでの米国における性別および人種的な職業分離から生じる社会福祉的な損失を探索する。特性を調整した後、不利な立場にある集団の相対的な大きさ　(発生率)、その損失の大きさ　(強度)、およびその集団間における不平等を考慮したものを含む様々な指標によると、損失は南部および西部よりも北東部で低い。西部は最も (条件付きの) 損失が大きいが、この現象の強度は南部や中西部とはほとんど変わらない。