Working Paper Series

Mapping the occupational segregation of white women in the U.S.: Differences across metropolitan areas

Olga Alonso-Villar
Coral del Río

ECINEQ WP 2015 - 352

ECINEQ 2015 - 352
January 2015

www.ecineq.org

Mapping the occupational segregation of white women in the U.S.: Differences across metropolitan areas*

Olga Alonso-Villar†
Universidade de Vigo, Spain

Coral del Río
Universidade de Vigo, Spain and EQUALITAS

Abstract

This paper seeks to investigate the occupational segregation of white women in the U.S. at the local labor market level, exploring whether the segregation of this group is a homogeneous phenomenon across the country or there are important disparities in the opportunities that these women meet with across American urban areas. An important contribution of this paper is that, apart from quantifying the extent of segregation it also assesses the consequences of that segregation taking into account the "quality" of occupations that the group tends to fill or not to fill. The analysis shows that between 20% and 40% of white women working in a metropolitan area would have to shift occupations to achieve zero segregation in that area. Differences regarding the nature of that segregation are even stronger. In some metropolitan areas, the uneven distribution of white women across occupations brings them a per capita monetary gain of about 21% of the average wage of the area while in other metropolitan areas this group has a per capita loss of nearly 11%.

Keywords: Occupational segregation, well-being, metropolitan areas, race, gender, U.S.

JEL Classification: R23, J15, J16, J71, D63.

*We gratefully acknowledge financial support from the *Ministerio de Economía y Competitividad* (ECO2013-46516-C4-2-R and ECO2011-23460) and FEDER.

†**Corresponding author**: Universidade de Vigo, Facultade de CC. Económicas, Departamento de Economía Aplicada, Campus Lagoas-Marcosende s/n, 36310 Vigo, Spain. Tel.: +34 986812507; fax: +34 986812401; email: ovillar@uvigo.es.

1. Introduction

Women and men occupy different positions in labor markets all over the world and also in the United States. Women tend to concentrate in jobs with lower wages, authority, and chances of promotion (Reskin and Bielby, 2005). In 2012, the median weekly earnings of women working full time was about 81% that of their male counterparts, a value that drops to 73% when focusing on workers with bachelor's degrees (U.S. Bureau of Labor Statistics, 2013). This average percentage masks, however, the particular situation of the different racial/ethnic groups, which ranges from 71% in the case of Asians to 90% in the case of blacks.

Many scholars concur that occupations play an important role in generating social stratification. Mouw and Kalleberg (2010) document that after adjusting for individual characteristics, polarization between occupations explains a large proportion of the increase in wage inequality that took place in the U.S. between 1992 and 2008. Occupational segregation by gender—that is, the fact that women and men work in different occupations— also helps to explain a large part of the gender pay gap (Peterson and Morgan, 1995).

When analyzing occupational segregation by gender, one should keep in mind that this phenomenon does not affect all racial/ethnic groups equally (Hegewisch et al., 2010; Mintz and Krymkowski, 2011). Moreover, the effect of gender segregation on the earning gap of women is also racially differentiated (Cotter et al., 2003, Del Río and Alonso-Villar, 2015). Consequently, when it comes to analyzing labor inequalities in general and occupational segregation in particular, special attention should be given to the intersection of gender and race/ethnicity because both contribute to shaping and maintaining inequalities (Browne and Misra, 2003).

The aim of this paper is to investigate the occupational segregation of a particular gender-race group, that of white women, at the metropolitan area level. Despite sharing gender roles, women of different races/ethnicities are exposed to different cultural stereotypes and occupy different economic and social positions. Thus, black women had greater incentives to incorporate into the labor market earlier than white women did (lower incomes, high black male unemployment, and paid work less socially stigmatized). On the other hand, the educational attainments of white women, which were traditionally higher than those of black women, have increased at a stronger pace, especially from 1980 onwards (McDaniel et al.

2011), which explains the educational gap that still exists between these two groups.[1] White women combine the privilege of being white and the disadvantage of being women, which makes them an interesting group for study.

The monetary loss of white women derived from its overrepresentation in some occupations and its underrepresentation in others was estimated to be close to zero at the national level in the late 2000s (Del Río and Alonso-Villar, 2015). In other words, the disadvantage this group derived from its occupational segregation was relatively small at the national level. This paper seeks to unveil the situation of white women at a subnational scale by exploring the segregation of this group in the local labor markets in which they work, something that can be done because this is a group with an important presence everywhere in the country.

Using the Integrated Public Use Microdata Series (IPUMS) 5-year sample of the 2007-2011 American Community Survey, this paper estimates the segregation level of white women across metropolitan areas. As opposed to other studies that are based on pair-wise comparisons between groups (e.g., white women versus white men, white women versus black women, and so on) and calculate an index—mainly the index of dissimilarity—for each of these comparisons, we use segregation measures that permit us to offer a single value for white women as the occupational sorting of this group is compared with the occupational structure of the economy (Alonso-Villar and Del Río, 2010). Our results based on 273 metropolitan areas show substantial variation across areas. The proportion of white women working in a metropolitan area who would have to shift occupations to achieve zero segregation without changing the occupational structure of the area ranges between 20% and roughly 40%.

An important contribution of this paper is that, apart from quantifying the extent of segregation at a subnational scale, it assesses it by taking into account the "quality" of occupations that white women tend to fill or not to fill, which here is proxied by the average wage. A high concentration of the group in a few occupations can be appraised as something good or bad for the group depending on those occupations' wages. For that purpose, this paper uses two measures recently proposed in the literature (Del Río and Alonso-Villar, 2014, 2015). One of them represents the monetary loss or gain of white women associated with their occupational segregation as a proportion of the average wage of the metropolitan area in

[1] The educational level of white women is, however, lower than that of Asian women. Thus, in 2010, 42% of white women ages 25-29 attained at least a bachelor's degree while the corresponding figure for Asian women was 56% (Wang and Parker, 2011).

which they work. According to this measure, the situation of white women ranges from a disadvantage of nearly 11% of the average wage of the metropolitan area to an advantage of 21%. The other measure that we use takes a step further by quantifying the well-being gain/loss of white women associated with its occupational sorting. This measure, which incorporates distributive value judgments that are in line with those conducted in the literature on income inequality, corroborates these spatial disparities.

The paper is structured as follows. Section 2 presents a brief background of the topic and explains how this paper extends the literature. Section 3 introduces the methodology that is used in Section 4 to explore the extent and consequences of segregation for white women across metropolitan areas. Section 5 goes one step further by attempting to explain the disparities that exist across areas. By undertaken both counterfactual and regression analyses, it investigates whether the spatial disparities that exist in the gains/losses of white women associated to their segregation arise from territorial differences in a) the educational level of white women, b) the gender-race composition of the labor force, c) the relative pay of occupations, d) the industrial structure, and e) the state in which the area is located. Finally, Section 6 offers the main conclusions.

2. What Do and Don't We Know about Occupational Segregation?

There is evidence that occupational segregation by gender dropped substantially in the second half of the 20th century, especially in the 1970s and 1980s, but this process seems to have come to a halt at the beginning of the 21st century (Beller 1985; Bianchi and Rytina, 1998; Levanon et al., 2009; Blau et al., 2013; Cohen, 2013). In other words, segregation by gender has not vanished despite the advances of previous decades. In 2010, four out of five women working full time were employed in occupations in which at least 75% of their workers were women; a similar situation, i.e., a high degree of masculinization, affected five out of ten men (Hegewisch et al., 2011). Moreover, when ranking occupations according to the percentage of female workers, "the median occupation for men is 25% female" and the "median occupation for women is 67% female" (Cohen, 2013, p. 890). In other words, half of men work in occupations where women represent less than 25% of workers and half of women work in occupations in which more than 67% of their workers are women.

Occupational segregation is not a minor issue. As mentioned above, it plays an important role in explaining the gender wage gap (Peterson and Morgan, 1995; Cotter et al., 1997; Gauchat et al., 2012). This is so because women tend to concentrate in occupations with lower wages, and this occurs even after controlling for education (Del Río and Alonso-Villar, 2015). Hegewisch et al. (2010) estimate that median earnings in low-skilled female-dominated occupations are about 74% of what workers in male-dominated occupations of the same skill receive. This percentage decreases to 67% in the case of high-skilled occupations.

But segregation by gender does not impact all races/ethnicities in the same manner; it seems to have a larger effect for Hispanics and a smaller one for Asians than it has for whites and blacks (Hegewisch et al., 2010; Mintz and Krymkowski, 2011). Likewise, segregation by race/ethnicity does not affect women and men equally; differences in segregation tend to be lower among female groups than among male groups (Spriggs and Williams, 1996; Reskin et al., 2004; Alonso-Villar et al., 2012). Consequently, both gender and race/ethnicity should be taken into account if one is interested in exploring the occupational segregation of a group.

With respect to white women, there is evidence that the occupational segregation of this group substantially decreased at the national level in the second half of the past century, although it has remained almost stagnant since 1990 (Del Río and Alonso-Villar, 2015). This reduction of segregation, which was also shared by women from other races, did not allow any female group to reach a neutral position in the labor market up to 1990; all female groups had monetary losses associated with their occupational distribution. Things started to change in the 2000s for Asian women—who obtained gains rather than losses—but not for other women. As mentioned above, in 2010, white women still had monetary losses associated with their occupational sorting at the national level, although they were relatively small (Del Río and Alonso-Villar, 2015).

By examining the segregation of white women at the local labor market level, this paper extends the literature in several ways. First, scholars have traditionally dealt with the analysis of segregation between women and men, and it is only recently that this literature has started to pay attention to the crossing of gender and race/ethnicity (Tomaskovic et al., 2006; Reskin, 1999; Hegewisch et al., 2010; Mintz and Krymkowski, 2011).[2]

Second, occupational segregation has been mostly estimated at the national level and there has been little inquiry into this issue at a subnational scale (Abrahamson and Sigelman, 1987; Lorence, 1992; Gradín et al., 2015), despite the fact that the situation of women may depend

[2] Pioneer works in this area are Albelda (1986) and King (1992), which distinguished between white and black women. The segregation of Hispanic and Asian women is a more recent topic.

on the characteristics of the local labor market in which they work (Semyonov and Scott, 1983; Jones and Rosenfeld, 1989; Cohen and Huffman, 2003; Cotter et al., 2003; Alonso-Villar et al., 2013). It therefore seems convenient to explore whether segregation at the national level reflects the real experience of white women.[3]

Third, another way in which this paper departs from the usual literature has to do with how segregation measurement is approached. To quantify the segregation of a group, most scholars compare the distribution of that group across occupations with the distribution of another group, mainly that of white men. But one might think that white women are unevenly distributed across occupations not only when they do not work in white male-dominated occupations but also when they are underrepresented in black female-dominated occupations black male-dominated occupations, Hispanic female-dominated occupations and so on, whether this underrepresentation is something bad or good for white women. For this reason, in quantifying the segregation of white women, this paper follows the approach developed by Alonso-Villar and Del Río (2010), according to which the group is said to be segregated so long as it departs from the occupational structure of the economy, whether this segregation is due to departures of white women from men of their own race, from other men, or from minority women.

Apart from analyzing whether there are spatial differences in the segregation level of white women, this paper also seeks to unveil whether the nature of that segregation is homogenous across the country. The concentration of a group in a few occupations can bring it advantages or disadvantages, depending on whether the group fills either high- or low-paid occupations. So far, only a few papers have quantified the gains/losses of a group in association with its segregation (Alonso-Villar and Del Río, 2013; Del Río and Alonso-Villar, 2014, 2015), and they have done so at the national level. Therefore, no disparities among metropolitan areas have yet been shown.

With respect to the role that occupational segregation plays in explaining the earning gap of women, the literature has also addressed this issue mainly at the national level and analyses at the metropolitan area level are scarce (Cotter et al., 2003; Reid et al., 2007). This paper extends that literature by quantifying for each metropolitan area the earning gap of white women that is derived from their occupational segregation.

[3] Semyonov et al. (2000) dealt with segregation by race rather than gender at the metropolitan area level. In a recent paper, Perales and Vidal (2013) show the importance of measuring segregation by gender at the local level in the United Kingdom.

3. Methodology

The index of dissimilarity—the most popular segregation measure—has been extensively used to quantify the discrepancy between the distribution of women and men across occupations. One could use this index to quantify the extent to which the distribution of white women departs from that of white men, but that would imply overlooking the discrepancies between the distribution of white women and those of minority men and women. The index of dissimilarity could also be used to calculate the segregation between white women and other groups but, by doing so, one would not have a single segregation value for white women but a value for each of these pairwise comparisons, which is especially cumbersome in a territorial analysis.

Alternatively, in this paper we calculate the segregation of white women by comparing its occupational sorting with the occupational structure of the economy. This means that white women are segregated so long as they are overrepresented in some occupations and underrepresented in others, whether those latter occupations are filled by white men, black women, black men, Hispanic women, or any other group. This approach was formally developed by Alonso-Villar and Del Río (2010), who defined several measures to quantify the segregation of a group in a multigroup context and explored their properties. To calculate the segregation of white women in each metropolitan area, we use two of their measures:

$$\Phi = \sum_j \frac{f_j}{F} \ln\left(\frac{f_j / F}{t_j / T}\right) \text{ and} \tag{1}$$

$$D = \frac{1}{2} \sum_j \left| \frac{f_j}{F} - \frac{t_j}{T} \right| , \tag{2}$$

where f_j denotes the number of white women in occupation j, t_j is the number of jobs in that occupation, $F = \sum_j f_j$ is the number of white women, and $T = \sum_j t_j$ is the total number of jobs. Both indexes satisfy some basic properties (Alonso-Villar and Del Río, 2010). Thus, for example, these indexes are not affected by the size of the group or the size of the economy, which makes it possible to compare the segregation of white women across metropolitan areas. The use of two rather than only one measure will allow us to check for robustness in our results.

Index Φ, which ranges from a minimum of 0 to a maximum of $\ln(T)$, is related to the Theil index used in the literature of income inequality and takes into account distributive value judgments that are in line with those conducted in that literature. Thus, for example, when some white women move from one occupation to another of the same size in which they have a lower representation, the index always decreases. This index is consistent with the mutual information index proposed by Frankel and Volij (2011) to quantify overall segregation in a multigroup context (i.e., this overall index can be written as the weighted average of the segregation, according to expression (1), of each of the mutually exclusive groups into which the economy is partitioned with weights equal to their demographic shares).

Index *D*, which ranges from 0 to 1, was initially proposed by Moir and Shelby Smith (1979) to measure the segregation of women in Australia, although these authors did not explore its properties or its usefulness in a multigroup context. In a dichotomous context, this index is consistent with the index of dissimilarity.[4] This index is also consistent with both the modified version of the index of dissimilarity proposed by Karmel and MacLachlan (1988) in a dichotomous context and the extended version developed by Silber (1992) in a multigroup context (Alonso-Villar and Del Río, 2010). An advantage of this index, not unveiled so far, is that it permits a clear economic interpretation. In fact, if we follow the same steps as Karmel and MacLachlan (1988) took for interpreting their modified version of the index of dissimilarity, we can easily show that *D* represents the percentage of white women that would have to change occupations so as to make the segregation of this group disappear (while keeping the occupational structure of the economy unaltered).

To prove this, note that if $a=\frac{F}{T}$ is the proportion of white women in the economy and *j* is an occupation in which white women are underrepresented, then $at_j - f_j$ white women would have to move into that occupation (while $(t_j - f_j)-(1-a)t_j$ persons from other groups would have to move out of it) in order for white women not to be underrepresented there (without altering the size of that occupation). On the contrary, if white women are overrepresented in occupation *j*, then $f_j - at_j$ white women would have to move out while $(1-a)t_j-(t_j - f_j)$ persons from other groups would have to move in. Therefore, in each occupation the total

[4] The index of dissimilarity in the case of segregation by gender can be written as the weighted average of the segregation of women, according to expression (2), and the segregation of men, with weights equal to the demographic shares of the groups divided by twice the product of these shares (Alonso-Villar and Del Río, 2010).

number of persons moving in or out is equal to $2\left|f_j - at_j\right|$. Given that if we sum over all occupations the people who move in and out we would be double counting, we must count only those who leave an occupation. Therefore, $\sum_j \left|f_j - at_j\right|$ represents the number of people who would have to change occupations for white women to have zero segregation. Taking into account that in each occupation the number of white women moving in is equal to the number of individuals from other groups moving out (and *vice versa*), $D = \frac{1}{2}\sum_j \left|\frac{f_j}{F} - \frac{t_j}{T}\right| = \frac{1}{2F}\sum_j \left|f_j - at_j\right|$ can be interpreted as the proportion of white women who would have to switch occupations to eliminate the segregation of this group.

But segregation alone does not permit us to assess the position of a group in the labor market because this position depends not only on whether the group has access to all occupations but also the "quality" of occupations that the group tends to fill or not fill. To assess the consequences of segregation taking into account the wages that are associated with occupations, we use two different measures recently proposed in the literature:

$$\Psi = \sum_j \left(\frac{f_j}{F} - \frac{t_j}{T}\right) \ln\left(\frac{w_j}{\overline{w}}\right) \text{ and} \tag{3}$$

$$\Gamma = \sum_j \left(\frac{f_j}{F} - \frac{t_j}{T}\right) \frac{w_j}{\overline{w}}, \tag{4}$$

where w_j is the (average) wage of occupation j and $\overline{w} = \sum_j \frac{t_j}{T} w_j$ is the average wage of the economy. The first index measures the *per capita* well-being gain or loss of white women associated with their segregation (Del Río and Alonso-Villar, 2015). The second index measures the *per capita* monetary gain or loss of white women for being underrepresented in some occupations and overrepresented in others, i.e., derived from their segregation (Del Río and Alonso-Villar, 2014). Both indexes satisfy several good properties. Thus, they are equal to zero when either white women have no segregation or all occupations have the same wage. They increase when white women move into occupations that have higher wages than those they have left behind. They differ, however, in some aspects.

The advantage of Γ is its clear economic interpretation—it measures the *per capita* monetary gain/loss of the group as a proportion of the average wage of the economy. In addition, it can be used to determine how much of the earning wage gap of the group is associated with its segregation. As shown by Del Río and Alonso-Villar (2015), if we denote by $\overline{w}^f$ the average wage of white women and by w_j^f the average wage of white women in occupation *j*, the earning gap ratio of this group, *EGap*, can be broken down into two terms:

$$EGap = \left(F\overline{w}^f - F\overline{w}\right)\frac{1}{F\overline{w}} = \underbrace{\left[\sum_j f_j \left(w_j^f - w_j\right)\right]\frac{1}{F\overline{w}}}_{\Delta} + \underbrace{\sum_j \left(\frac{f_j}{F} - \frac{t_j}{T}\right)\frac{w_j}{\overline{w}}}_{\Gamma}, \qquad (5)$$

one associated with the occupational segregation of the group, represented by Γ, and the other associated with within-occupation wage disparities with respect to other groups, denoted by Δ. By using this expression, we can easily determine how much of the earning gap ratio of white women is attributed to their occupational segregation.

On the other hand, the advantage of Ψ is that it takes into account distributive value judgments that are in line with those conducted in the income distribution literature. This means that, for example, when some white women move from one occupation into another with a $100 higher wage, the lower the wage of the occupation left behind, the higher the effect of this movement on the index. In other words, for this index the occupational advances of those who work in bad occupations are more important that the advances of those working in good occupations. In addition, the effect of a white women moving into an occupation with a $100 wage of increase is lower than that of 10 white women moving into an occupation with a $10 increase. In other words, small improvements for many white women are more important than large improvements for only a few.

In our analysis we use both measures to assess the occupational sorting of white women. One will permit us to express the consequences of segregation for white women as a proportion of the average wage of the economy while the other will allow us to measure the well-being gain/loss of these women with a measure that takes into account value judgments that are in line with those used in the literature on income distribution. The use of two indexes instead of one will allow us to check the robustness of our findings. For exposition purposes, in our empirical analysis, the values of these indexes are given multiplied by 100.

4. The Extent and Consequences of Segregation

4.1 Dataset

We use the 5-year 2007-11 sample drawn from the Integrated Public Use Microdata Series (IPUMS), which is based on the American Community Survey (Ruggles et al., 2010). The analysis is undertaken using both a detailed occupational breakdown (with 519 categories as opposed to the 42 categories used in Abrahamson and Sigelman, 1987, and the 144 used in Lorence, 1992) and a more aggregated one (with 94 categories).[5] In order to have reliable results, the analysis based on the 519 titles is undertaken only for the 80 metropolitan areas where white women have at least 5,190 observations in the sample. The analysis based on the 94 titles allows us to explore a larger number of metropolitan areas because using a similar criterion we find 273 areas (those with at least 940 white female observations). The definition of metropolitan area (MA for short) used is based on the 2000 metropolitan boundaries and refers to individuals' place of work.

We proxy the wage of each occupation by the average wage per hour trimming the tails of the hourly wage distribution to prevent data contamination from outliers. Thus, we compute the trimmed average in each occupation eliminating all workers whose wages are zero or who are situated below the first or above the 99th percentile of positive values in that occupation.[6]

4.2 Selected Metropolitan Areas with Detailed Occupational Titles

We start our comparative analysis using a disaggregated occupational classification, which consists of 519 occupational titles. As mentioned above, to have reliable results we only study those areas with enough white women in the sample. This implies restricting the analysis to 80 MAs.[7] Table 1 shows the segregation level of white women in each of these areas, as well as at the national level, according to the indexes given in Section 3 (Φ and D). The monetary gains/losses and well-being gains/losses of white women associated with their segregation are also given in that table (Ψ and Γ values are given multiplied by 100).

---

[5] The occupation "military specific occupations" is not included in our analysis.

[6] Some individuals in the sample do not have a wage (they represent 5.4% of the observations). To account for the same number of individuals in both the segregation measurement and the assessment of that segregation, to those without a wage or with wages in the trimmed tails, we imputed them a wage equal to the average wage of individuals of the same gender-race group (white women, white men, minority women, or minority men), if any, who work in the same occupation and MA.

[7] There are a few large MAs for which we do not have figures in the dataset (as is the case of Denver and Miami).

At the national level, $D = 0.28$, which means that 28% of white women would have to switch occupations for them to have zero segregation, i.e., to be evenly distributed across occupations (without altering the occupational structure of the economy). The situation at the local level is not too different, although there are some differences between the MAs with the lowest and highest segregation. The proportion of white women who would have to change occupations to achieve zero segregation ranges from 25% in Washington, D.C., and Sacramento to 36% in New Orleans. When using index Φ instead, we find that the level of segregation decreases slightly at the national level ($\Phi = 0.24$) and shows more dispersion across MAs (Φ ranges from 0.22 to 0.42). The correlation between both indexes at a MA level is very high, 0.98, which means that they produce similar results.

Differences across MAs are much more intense when assessing the segregation of white women. Despite white women having a *per capita* loss close to zero at the national level ($\Gamma = -1.6$), the situation of these women strongly varies across areas. Some MAs have a much more negative value while others have high positive values.[8] Thus, the *per capita* gain of white women in Los Angeles associated with their occupational sorting is equal to 14.4% of the average wage in that area ($\Gamma = 14.4$). The *per capita* advantage is also high in New York ($\Gamma = 9.7$), San Antonio ($\Gamma = 8.8$), San Francisco ($\Gamma = 6.5$), and Houston ($\Gamma = 6.2$). At the other extreme we find Pittsburg, Fort Wayne, Detroit, Knoxville, Dayton-Springfield, and Salt Lake City, which show *per capita* losses for white women that are around 7% ($\Gamma = -6.8$ in Dayton-Springfield and $\Gamma = -7.8$ in Pittsburg). The differences among MAs according to index Ψ, which as opposed to Γ takes into account distributive value judgments that are in line with those conducted in the income distribution literature, are also intense. The value of Ψ ranges between -7.5 and +15.5. The correlation between Ψ and Γ is 0.99, which suggests that our results are quite robust.

[8] The density function of Γ for these MAs is shown in the Appendix (Figure A1). The mean is -1.7 and the standard deviation 4.3.

	519 Occupational Titles				94 Occupational Titles				EGap
MAs	Φ	D	Γ	Ψ	Φ	D	Γ	Ψ	
Akron, OH	0.27	0.29	-6.04	-5.70	0.20	0.25	-2.79	-3.55	-13.59
Albany-Schenectady-Troy, NY	0.25	0.27	-4.37	-3.68	0.19	0.24	-1.96	-2.01	-9.05
Allentown-Bethlehem-Easton, PA/NJ	0.28	0.29	-5.48	-4.84	0.20	0.25	-2.01	-2.66	-12.20
Atlanta, GA	0.27	0.29	0.28	1.64	0.22	0.26	2.51	3.08	-4.51
Austin, TX	0.29	0.29	1.64	3.55	0.23	0.26	4.02	4.94	-4.18
Baltimore, MD	0.24	0.27	-1.52	-0.53	0.20	0.24	0.80	0.96	-5.57
Birmingham, AL	0.33	0.32	0.10	1.14	0.26	0.28	2.34	2.51	-7.18
Boston, MA	0.22	0.26	-3.57	-2.61	0.18	0.23	-1.13	-0.98	-9.52
Buffalo-Niagara Falls, NY	0.24	0.27	-4.68	-4.27	0.18	0.24	-1.97	-2.43	-10.17
Charlotte-Gastonia-Rock Hill, SC	0.28	0.29	-2.17	-1.31	0.22	0.26	1.04	1.00	-7.86
Chicago-Gary-Lake, IL	0.26	0.28	-0.75	0.60	0.22	0.25	1.81	2.09	-5.66
Cincinnati, OH/KY/IN	0.24	0.27	-5.37	-4.88	0.19	0.24	-2.78	-3.00	-11.55
Cleveland, OH	0.24	0.27	-5.81	-5.35	0.19	0.24	-2.81	-3.29	-12.25
Columbia, SC	0.32	0.31	0.68	1.33	0.25	0.27	2.96	2.49	-4.86
Columbus, OH	0.22	0.26	-3.59	-3.03	0.18	0.24	-1.27	-1.41	-9.87
Dallas-Fort Worth, TX	0.32	0.31	2.85	5.38	0.27	0.28	5.21	6.71	-1.53
Fort Worth-Arlington, TX	0.32	0.32	-0.51	1.07	0.27	0.29	2.30	2.66	-5.97
Dayton-Springfield, OH	0.24	0.28	-6.84	-6.14	0.18	0.24	-3.06	-3.67	-13.19
Detroit, MI	0.24	0.28	-7.61	-7.51	0.20	0.25	-4.58	-5.43	-14.19
Fort Lauderdale-Hollywood-Pompano Beach, FL	0.30	0.30	2.09	3.52	0.23	0.26	4.58	4.73	0.78
Fort Wayne, IN	0.29	0.30	-7.66	-6.70	0.22	0.27	-3.03	-4.12	-13.48
Grand Rapids, MI	0.27	0.30	-6.11	-5.43	0.21	0.27	-2.27	-2.98	-12.34
Greensboro-Winston Salem-High Point, NC	0.28	0.30	-0.67	0.10	0.23	0.27	2.01	1.79	-5.32
Greenville-Spartenburg-Anderson, SC	0.33	0.33	-4.54	-4.19	0.26	0.30	-0.30	-1.13	-9.98
Harrisburg-Lebanon-Carlisle, PA	0.25	0.28	-6.07	-5.66	0.19	0.24	-3.13	-3.56	-11.39
Hartford-Bristol-Middleton-New Britian, CT	0.25	0.27	-0.37	0.62	0.20	0.24	1.47	1.68	-4.19
Houston-Brazoria, TX	0.37	0.34	6.18	8.67	0.32	0.31	8.19	9.63	1.33
Indianapolis, IN	0.24	0.28	-3.91	-3.20	0.19	0.25	-0.76	-1.32	-10.27
Jacksonville, FL	0.26	0.28	-3.13	-2.48	0.20	0.24	-0.30	-0.57	-8.70
Kansas City, MO-KS	0.25	0.28	-4.25	-3.70	0.20	0.25	-1.36	-1.66	-11.36
Knoxville, TN	0.29	0.30	-7.56	-6.45	0.23	0.27	-3.45	-3.75	-15.10
Las Vegas, NV	0.30	0.31	2.93	3.67	0.25	0.28	4.27	4.50	-1.25
Little Rock-North Little Rock, AR	0.30	0.30	-0.71	-0.02	0.23	0.27	2.05	1.72	-4.55
Los Angeles-Long Beach, CA	0.35	0.33	14.43	15.52	0.30	0.30	14.94	15.23	15.78
Orange County, CA	0.33	0.32	4.14	6.67	0.28	0.28	5.87	7.38	2.80
Louisville, KY/IN	0.25	0.28	-4.42	-3.74	0.19	0.24	-1.25	-1.52	-10.40
Madison, WI	0.23	0.26	-5.50	-4.85	0.17	0.23	-2.73	-3.02	-10.26
Memphis, TN/AR/MS	0.36	0.34	2.31	4.09	0.29	0.30	5.05	5.56	-2.62
Milwaukee, WI	0.25	0.28	-3.60	-2.81	0.20	0.24	-0.04	-0.56	-9.02
Minneapolis-St. Paul, MN	0.22	0.26	-3.99	-3.35	0.18	0.23	-1.53	-1.81	-10.04
Monmouth-Ocean, NJ	0.28	0.29	-6.30	-4.75	0.22	0.26	-3.06	-2.53	-11.39
Nashville, TN	0.27	0.29	-2.75	-1.57	0.21	0.26	0.95	0.76	-8.46
New Orleans, LA	0.42	0.36	1.04	1.86	0.34	0.32	3.26	2.84	-6.06
New York-Northeastern NJ	0.29	0.30	9.71	11.96	0.24	0.27	10.70	11.99	9.01
Nassau-Suffolk, NY	0.28	0.30	-0.18	0.82	0.23	0.26	1.94	2.02	-3.38
Bergen-Passaic, NJ	0.33	0.32	-0.38	1.77	0.26	0.28	2.41	3.16	-2.81
Middlesex-Somerset-Hunterdon, NJ	0.31	0.31	-2.91	-1.61	0.25	0.28	-0.94	-0.26	-5.48
Newark, NJ	0.31	0.31	0.28	1.81	0.25	0.27	2.15	2.81	-2.22
Norfolk-VA Beach-Newport News, VA	0.30	0.31	-1.71	-1.40	0.24	0.27	0.87	0.30	-6.63
Oklahoma City, OK	0.30	0.31	-3.60	-2.12	0.23	0.27	-0.42	-0.54	-8.98
Orlando, FL	0.26	0.28	0.21	1.80	0.21	0.25	2.72	3.09	-4.22
Philadelphia, PA/NJ	0.25	0.27	-2.83	-2.14	0.20	0.25	-0.29	-0.47	-8.35
Phoenix, AZ	0.28	0.30	-0.04	1.30	0.23	0.27	2.31	2.60	-4.28
Pittsburgh-Beaver Valley, PA	0.25	0.28	-7.85	-7.45	0.20	0.25	-4.21	-4.96	-14.57
Portland-Vancouver, OR	0.24	0.27	-4.06	-3.13	0.19	0.24	-1.44	-1.56	-9.94
Providence-Fall River-Pawtuckett, MA	0.24	0.27	-1.53	-1.08	0.19	0.24	0.45	0.34	-5.54
Raleigh-Durham, NC	0.27	0.28	1.11	2.78	0.22	0.25	3.15	3.89	-2.50
Richmond-Petersburg, VA	0.28	0.29	-0.05	0.62	0.22	0.26	2.76	2.67	-5.62
Riverside-San Bernadino,CA	0.36	0.34	4.74	5.11	0.30	0.31	6.38	5.67	3.63
Rochester, NY	0.24	0.28	-4.69	-4.09	0.19	0.24	-2.08	-2.45	-10.54
Sacramento, CA	0.23	0.25	0.04	0.61	0.18	0.22	1.56	1.54	-3.29
St. Louis, MO	0.25	0.27	-6.15	-5.59	0.20	0.24	-2.90	-3.29	-13.09
Salt Lake City-Ogden, UT	0.28	0.30	-7.71	-6.71	0.23	0.27	-4.32	-4.47	-15.13
San Antonio, TX	0.33	0.31	8.81	9.39	0.26	0.27	9.90	9.55	7.68
San Diego, CA	0.29	0.30	2.88	4.45	0.24	0.27	4.77	5.44	0.79
San Francisco-Oakland-Vallejo, CA	0.26	0.28	6.53	8.48	0.20	0.24	7.87	8.83	5.20
Oakland, CA	0.30	0.30	3.85	5.18	0.24	0.27	5.22	5.67	3.06
San Jose, CA	0.36	0.34	-0.70	1.81	0.28	0.30	1.08	2.63	-1.98
Sarasota, FL	0.28	0.30	-2.15	-1.03	0.21	0.25	1.80	1.84	-7.18
Scranton-Wilkes-Barre, PA	0.26	0.29	-6.38	-6.06	0.20	0.25	-2.42	-3.50	-12.82
Seattle-Everett, WA	0.24	0.28	-5.62	-5.10	0.19	0.24	-3.30	-3.49	-11.42
Springfield-Holyoke-Chicopee, MA	0.24	0.27	-2.20	-1.65	0.19	0.23	0.92	0.14	-5.89
Syracuse, NY	0.25	0.28	-5.62	-4.99	0.20	0.25	-2.65	-3.12	-11.10
Tacoma, WA	0.28	0.29	-5.39	-5.21	0.22	0.25	-2.18	-3.23	-8.49
Tampa-St. Petersburg-Clearwater, FL	0.23	0.26	-2.23	-1.09	0.18	0.24	0.36	0.47	-7.07
Toledo, OH/MI	0.27	0.30	-6.48	-5.90	0.21	0.26	-2.60	-3.36	-12.76
Tucson, AZ	0.26	0.28	0.17	1.16	0.20	0.24	2.35	2.13	-2.48
Tulsa, OK	0.32	0.32	-5.66	-4.24	0.26	0.29	-2.43	-2.18	-11.77
Washington, DC/MD/VA	0.22	0.25	3.01	4.94	0.18	0.22	4.48	5.87	-1.72
West Palm Beach-Boca Raton-Delray Beach, FL	0.29	0.30	0.70	3.19	0.23	0.26	3.51	4.46	-3.36
US	0.24	0.28	-1.57	-0.59	0.21	0.25	1.01	1.04	-7.59

Table 1. Segregation level of white women (Φ and D), assessment of that segregation (Γ and Ψ are multiplied by 100), and earning gap ratio (*Egap*) in selected MAs, 2007-11

An important finding of our analysis is that measuring segregation alone—that is, quantifying the extent to which a group is unevenly sorted across occupations—may not say too much about the position of our group in the labor market. White women in some areas have a low segregation level and either a monetary loss associated with that segregation (Boston, Columbus, Madison, and Minneapolis) or a gain (Washington, D.C.). White women in other areas have an intermediate level of segregation and either important gains derived from that segregation (San Francisco and New York) or losses (Pittsburgh and Seattle). In other areas, they have a high segregation level and either a loss close to zero (San Jose) or even a gain (Los Angeles, Houston, San Antonio, and Riverside-San Bernardino). Therefore, dispersion in segregation levels may obscure important discrepancies in the nature of segregation that white women experience. In some MAs, the segregation of white women makes them an advantaged group, while in others it causes them a disadvantage.

4.3 Segregation at a Metropolitan Area Level with a Broad Occupational Classification

In order to have a wider geographic view of the extent and consequences of segregation faced by white women across American local markets, it seems convenient to enlarge the list of MAs considered in the analysis. This requires reducing the list of occupational titles to avoid biased values in our indexes derived from small samples of white women in some areas. Our list in this section, which includes 94 titles, is based on the minor group codes of the 2010 Standard Occupational Classification.

The price we have to pay to get this broader view of what happens in the country is that the segregation level and the consequences of that segregation may be less accurate (although homogenous across the country). To see what such a change in the occupational classification involves, we calculate our four indexes using these 94 titles for our selected MAs in order to compare them with those previously obtained using the 519 titles. The indexes based on the 94 titles are also shown in Table 1. We see that the levels of segregation change slightly, and the magnitude of the two segregation indexes tends to be lower with the less detailed classification because when aggregating occupation titles, the differences that may exist among the occupations are hidden. Despite this, the MAs in which white women are highly/minimally segregated tend to be the same. In fact, the correlation between D based on the 94 titles and D based on the 519 titles is 0.98. The correlation for index Φ is also 0.98. The losses of white women tend to be of a lower magnitude when using the 94 titles, but the correlation between both classifications is even higher for Γ and Ψ than it is for the indexes of segregation (0.99 and 1, respectively).[9]

All of this suggests that the rankings of MAs based on either the segregation level of white women or the consequences of that segregation remain almost unaltered when using the occupational classification based on 94 titles. From now on, our analysis uses that classification. As already mentioned, to avoid biases due to lack of observations in the sample, we only study those MAs with at least 940 white women in the sample. Therefore, in this section we study 273 MAs, which account for almost 77% of the employed population in the country and 73% of white women workers.

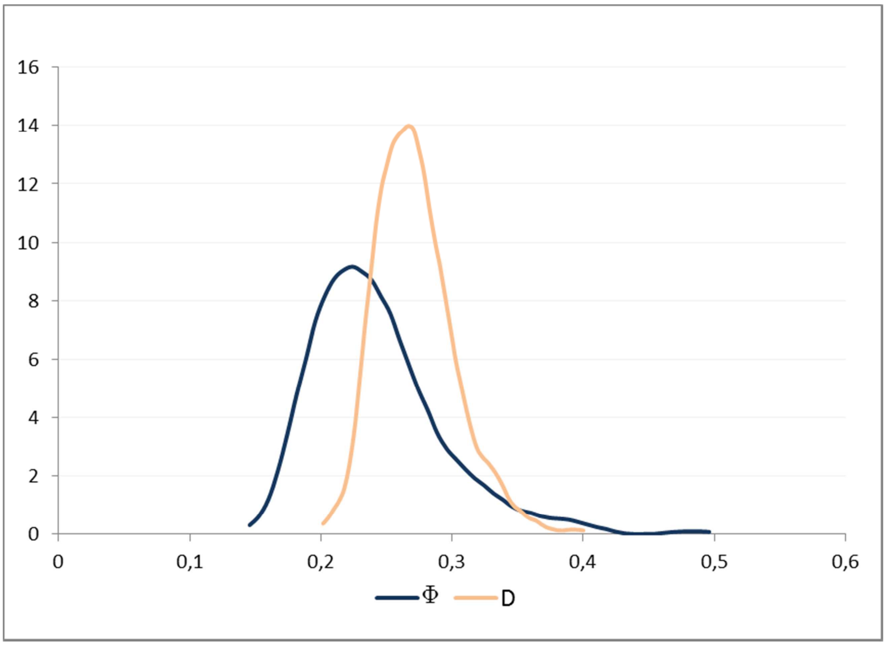


Figure 1. Segregation levels of white women across 273 MAs (indexes Φ and *D*): Density functions, 2007-11

Figure 1 shows the density function of the segregation level of white women across MAs for indexes Φ and *D*. According to *D*, between 20% and 40% of white women would have to switch occupations in the MA in which they work for this group to have no segregation. The range of values for index Φ is even wider (as also happened in the analysis based on the 519 occupational titles). The density function of index Φ is squatter and further to the left than that of *D*, although its right tail is larger. Therefore, with Φ the extent of segregation happens to be a more heterogeneous phenomenon. In some MAs, the level of segregation more than

[9] In Figure A1 in the Appendix, the density function of Γ for our selected MAs based on the 94 occupational titles is compared with the density function based on the 519 occupational titles. We see that the curve of the former is further to the right, which means that when using 94 occupations we are underestimating the losses of white women associated with their segregation. In fact, the mean when using the 94 titles is higher (0.9 as opposed to -1.7) although the standard deviation is lower (3.7 as opposed to 4.3).

doubles, or even triples, that of others. The variability of this index among MAs is similar to the variability that this index experiences at the national level when comparing 1960 and 2010 (Del Río and Alonso-Villar, 2015), which suggests that the territorial dimension is at least as important as the time dimension.[10]

Figure 2 shows the density function of the monetary gains/losses of white women across MAs derived from their occupational sorting (Γ). This chart also includes the density function of the earning gap of white women that arises from within-occupation differences with respect to other groups' wages (Δ) and the density function of the total earning gap derived from both segregation and within-occupation disparities (*EGap*).

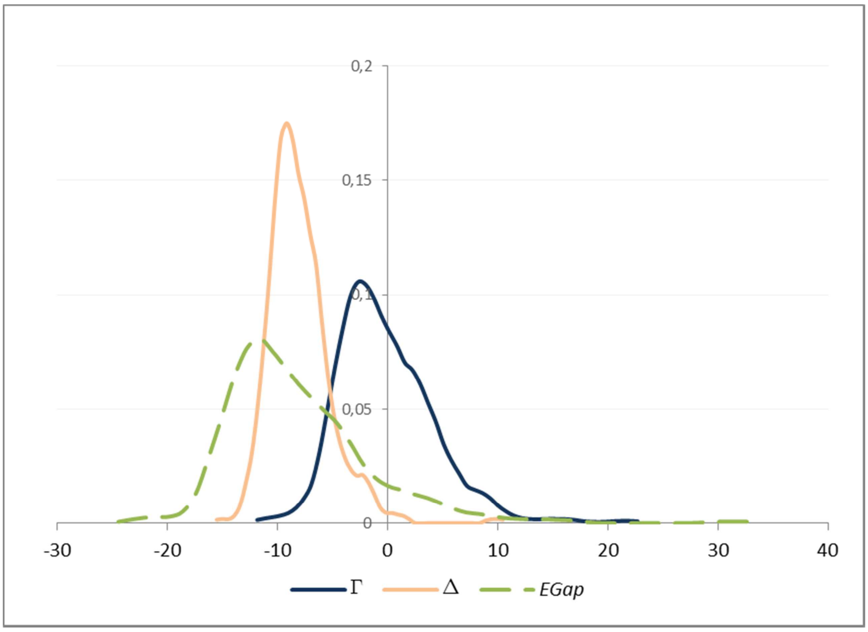


Figure 2. Total earning gap of white women (*EGap*) across 273 MAs and its components (Γ and Δ): Density functions, 2007-11

We see that white women have within-occupation wage disadvantages in almost all MAs—Δ takes negative values in virtually all areas. This means that white women tend to have lower wages than other workers who hold similar kinds of jobs. The earning gap of these women derived from their occupational distribution is more heterogeneous: Γ is positive in roughly half of the areas and negative in the other half (43% and 57%, respectively). The mean of this distribution is -0.15 and the standard deviation 4.3, which means that although the average loss is close to zero there are important discrepancies across areas.[11] The combination of both occupational sorting disadvantages and within-occupation wage disadvantages makes white

[10] Using the index of dissimilarity, Lorence (1992) also showed that spatial variability in segregation by gender can be more intense than variability across time.
[11] The value of Γ at the national level when using 94 titles is 1; see Table 1.

women have a positive earning advantage only in a few MAs, those where *EGap* is positive. In most MAs the *EGap* is negative, however.

The role that occupational sorting plays in explaining the earning gap of white women also varies across MAs (see Figure 3). In some areas, the occupational sorting of white women explains half of their earning gap. In others, the disadvantage of this group arises only for what occurs within occupations while in others the earning advantage is only due to their occupational sorting.

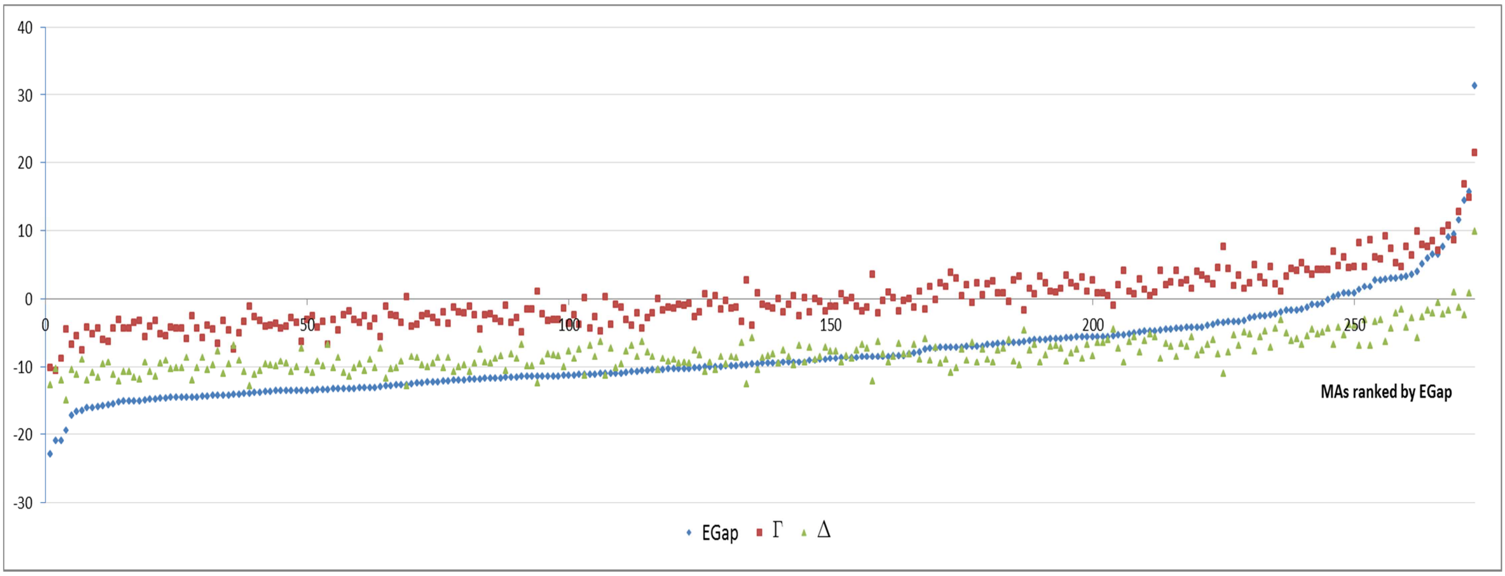


Figure 3. Total earning gap (*EGap*) of white women in each MA and its decomposition in segregation disadvantage (Γ) and within-occupation wage disadvantage (Δ); MAs ranked by their *EGap*: 273 MAs, 2007-11

To determine how many white women are affected by these losses/gains, in Figure 4 we show the percentage of white women who work in MAs in which the monetary gains/losses of this group associated with their segregation is above a certain threshold. We see that about 49% of white women work in MAs in which they experience losses from their occupational sorting (i.e., Γ is below zero), and 33% work in areas in which their gains are at least 2% of the average wage of the area (i.e., Γ is above 2). Only 10% of them work in areas where their advantage is at least 6% of the average wage of the area (i.e., Γ is above 6). For comparative purposes, the curve for white men has also been included in Figure 4. The chart reveals that the occupational sorting of white men always brings them gains: 100% of white men work in MAs in which they are advantaged and 51% work in areas in which they receive a gain of at least 9%.

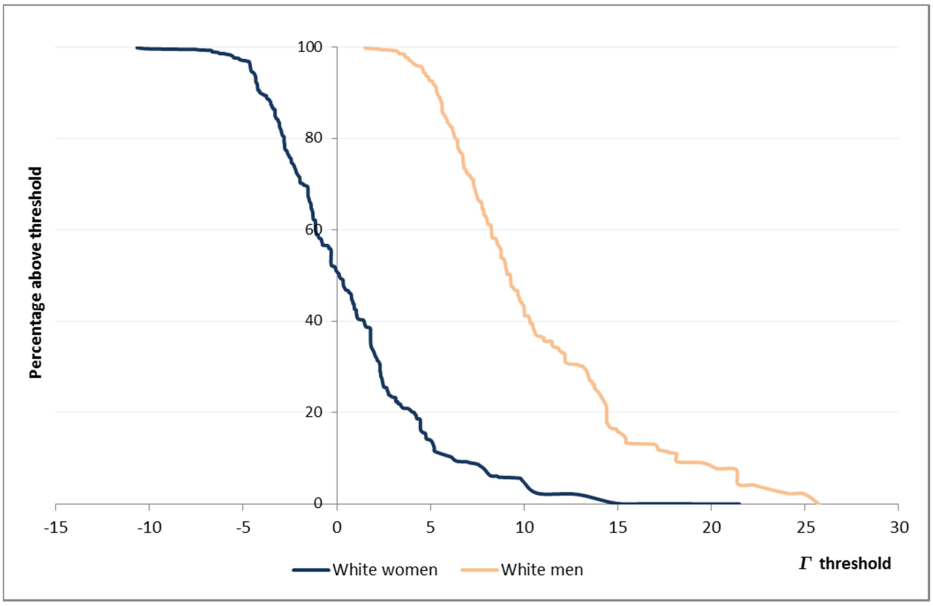


Figure 4. Percentage of white women (or alternatively, white men) working in MAs where Γ is above each threshold, 2007-11.

5. Exploring Differences across MAs

The previous section has unveiled the remarkable discrepancies that exist among MAs regarding the gains/losses of white women associated with their occupational segregation. We now take a step further to explore whether these disparities are the result of spatial differences in the educational achievements of white women, differences in the racial-gender composition of MAs, differences in the value of occupations across MAs, or spatial discrepancies in their industrial structures. We also investigate whether differences across MAs arise mainly as a consequence of disparities across states or there are instead important discrepancies within states.

To answer these questions, we first undertake counterfactual analyses so that we can determine the extent to which the distribution of index Γ across MAs changes when homogenizing by each of these variables separately. Second, we carry out a regression analysis to test whether these variables have explanatory power when taking all of them together.

5.1 Spatial Differences in the Education of White Women

Differences in the occupational segregation of white women among MAs may arise from differences in the characteristics that they bring to the labor market, among which human capital appears most important. For this reason, we start our analysis exploring whether the spatial discrepancies are the result of differences in the educational level of white women.

We distinguish four educational levels: less than a high school diploma, a high school diploma, some college, and a bachelor's degree. To investigate the role that education plays in explaining the disparities that exist in the gains/losses of white women across MAs, we recalculate index Γ for each MA using a counterfactual distribution (see the Appendix for a more technical description). This artificial distribution is built in such a way that, on the one hand, in each MA the proportion of white women who have a given level of education is forced be the same as that in the entire country, i.e., we make the educational composition of white women to be the same everywhere. On the other hand, in each MA we keep the distributions of the four educational groups of white women across occupations unaltered. This means that, the probability of a white woman with a given education level being in a certain occupation is the same in the counterfactual distribution as it is in the observed distribution.

When we calculate the *per capita* monetary gains/losses of white women using this counterfactual distribution, the differences among MAs can no longer be the result of spatial differences in the educational composition of white women because in our artificial population, the proportion of each educational group is the same everywhere. Spatial differences can only arise from disparities in the opportunities that the areas bring to the four educational groups of white women.

Comparing the monetary gains/losses of white women across MAs in the observed distribution with those in the counterfactual distribution, we find that the standard deviation decreases by 10% (the mean changes from -0.15 to 1.05). This suggests that education helps to explain the differences among areas but only partially.

Figure 5 displays the density function of index Γ for the 80 MAs we selected using the original data and also that of the counterfactual, denoted by Γ^*. Figure 6 gives the same information for the 193 remaining MAs.[12] We show the analyses for large and small MAs separately because their patterns are rather different.

[12] The density functions for the whole list of MAs are quite similar to those of the 193 MAs.

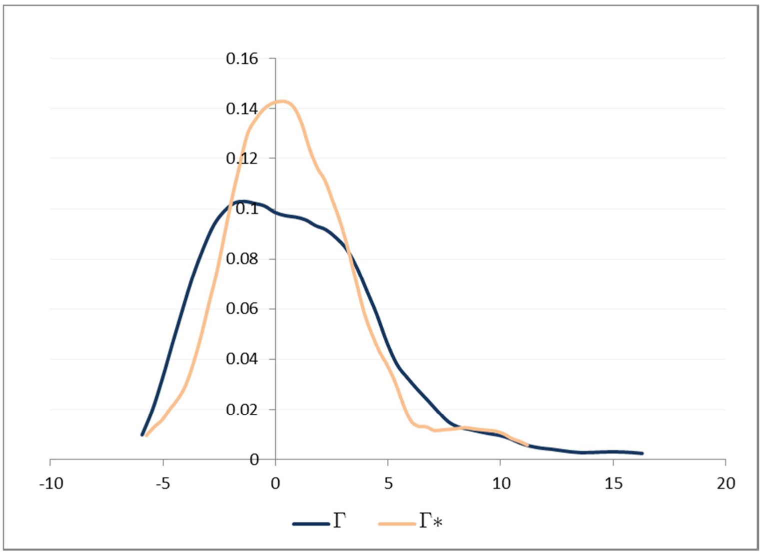


Figure 5. Monetary gains/losses of white women using the real data (Γ) and the education-counterfactual (Γ^*): Density functions for the 80 largest MAs, 2007-11

Figure 5 shows that the density function of Γ^* shrinks as compared to that of Γ. In other words, when we homogenize large MAs by education, the gains (and respectively, the losses) of white women in the areas in which they initially had advantages (and respectively, disadvantages) are not so large. The standard deviation of the gains/losses of white women for these areas decreases by around 20%, which means that a significant proportion of the disparities among large MAs seem to arise from education. In any case, discrepancies among large MAs are still persistent after the homogenization.

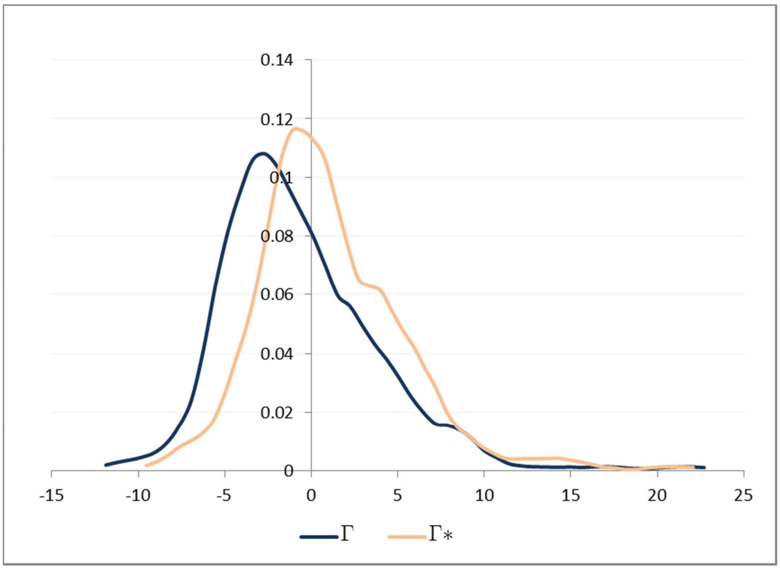


Figure 6. Monetary gains/losses of white women using the real data (Γ) and the education-counterfactual (Γ^*): Density functions for the 193 smallest MAs, 2007-11

The pattern for smaller MAs is quite different. The standard deviation in this case decreases by only 6%. This means that disparities among these areas barely depend on educational discrepancies. Figure 6 reveals that the density function of Γ^* is further to the right than that of Γ. This means that these MAs tend to have larger gains (or lower losses) when white women have the same educational composition everywhere. This is so because many small MAs have a lower proportion of white women with either some college or a bachelor's degree than the national average. Therefore, as one would expect, when the proportions of the highly educated group increase, the gains of white women as a whole also increase. In any case, Figure 6 reveals that even if the educational composition of white women were the same everywhere, we would still find important differences among MAs: Γ^* ranges between -10 and above +20. In other words, disparities among MAs derived from the occupational sorting of white women seem to go beyond spatial differences in educational achievements.

5.2 Spatial Differences in the Gender-Race Composition of the Labor Force

Another factor that may affect the monetary gains/losses of white women is the racial and gender composition of the area. The performance of this group in a local labor market may depend on the representation of other groups and on how the market ranks them (Semyonov et al., 2000; Ovadia, 2003). To put it another way, differences in the value of Γ among areas may be the result of differences in the proportions of white women, minority women, white men, and minority men working in the area. We labeled with Γ^* the monetary losses/gains that white women would have in this counterfactual distribution, i.e., if the shares of these four groups were the same everywhere (and equal to their shares in the whole country). The standard deviation of the monetary gains/losses of white women in this counterfactual distribution is 2.8, which implies a reduction of dispersion of around 35%.[13] In other words, the racial-gender composition of areas seems to explain an important share of the spatial disparities of white women's losses/gains.

Figure 7 plots both the value of Γ and $\Gamma^* - \Gamma$ for each of the 273 MAs, which have been ranked by their minority share in ascending order. This chart reveals that white women working in areas with a low proportion of minorities tend to be worse ($\Gamma < 0$) than those working in areas with large proportions of minorities ($\Gamma > 0$). When homogenizing by gender and race, white women in the former areas tend to improve ($\Gamma^* - \Gamma > 0$) while those in the latter tend to get worse ($\Gamma^* - \Gamma < 0$).

[13] The mean changes from -0.15 to 0.67, which means that the average gain/loss across areas is close to zero in both cases.

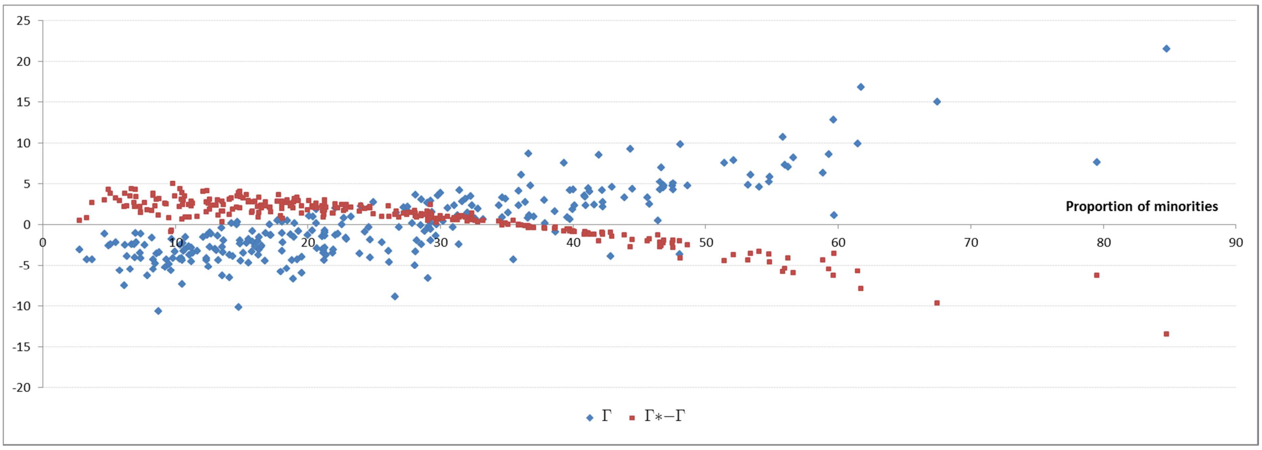


Figure 7. Gains/losses of white women using the real data (Γ) and their differences with respect to the gender-race-counterfactual ($\Gamma^* - \Gamma$): 273 MAs ranked by their minority share, 2007-11

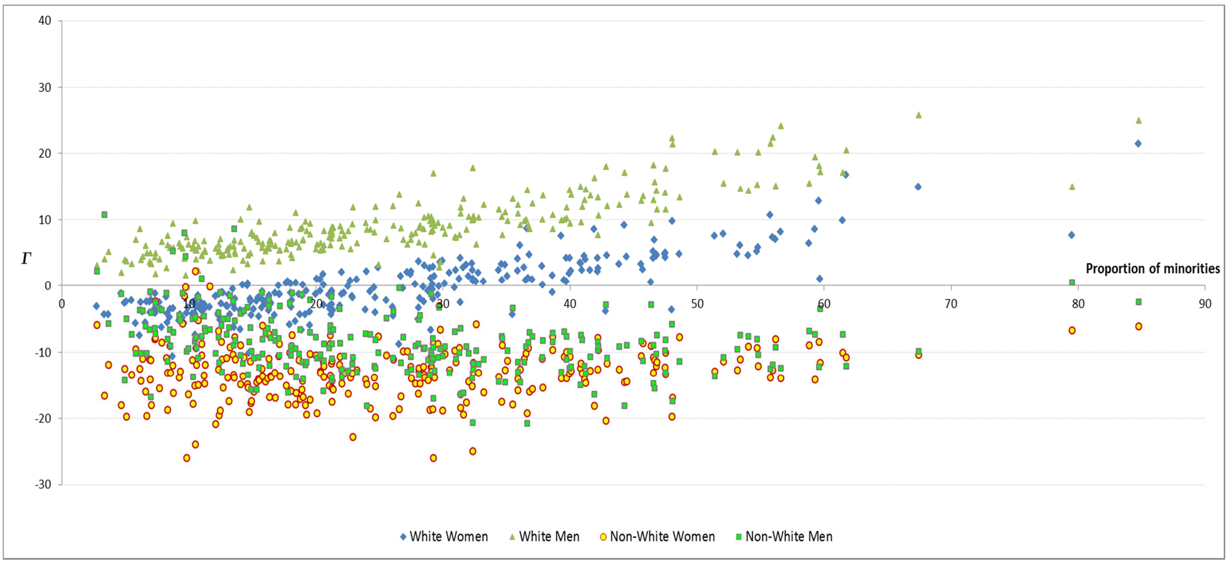


Figure 8. Gains/losses (Γ) of the four gender-race groups: 273 MAs ranked by their minority share, 2007-11

For comparative purposes, Figure 8 shows the value of Γ not only for white women, but also for white men, minority women, and minority men. The analysis shows that white women tend to have an intermediate position between white and minority men, while minority women tend to be the group with the largest losses (this pattern also occurs when working with a more disaggregated classification of occupations; see Figure A2 in the appendix). White women start to have advantages when the proportion of minority workers in the MA is about 20% (this percentage rises to roughly 40% when using 519 titles; see Figure A2). Below that level, only white men have advantages associated with their occupational sorting.[14]

[14] There are few exceptions, however. In some MAs, apart from white men, either minority women or men have gains as well. Thus, Hagerstown (MD) in the case of minority women and Johnstown (PA), Bloomington-Normal (IL), State College (PA), Kokomo (IN), Rochester (MN), Altoona (PA), Jackson (MI), and Honolulu

This finding is consistent with theories of labor market segmentation and the queuing process (Reskin and Roos, 1990; Kaufman, 2002). Employers might qualify workers according to the gender-racial/ethnic group to which they belong. This mechanism may interact with labor market segmentation and queuing processes that allocate "good" jobs to the advantaged group. An increase in the size of a disadvantaged group may benefit those with a higher position in the ranking because more low-paid jobs can be filled by the underprivileged group when advantaged groups move to better occupations.

5.3 Spatial Differences in the Relative Pay of Occupations

But index Γ depends not only on how white women are distributed across occupations as compared to other demographic groups but also on the relative wages of occupations ($\frac{w_j}{\bar{w}}$). To explore whether the disparities in the gains/losses of white women across areas arise from spatial variations in the relative wages of occupations, i.e., in the way some occupations are paid as compared to others, we compare the value of Γ in each MA with the value it would have if the relative wage of each occupation in that area were equal to the one that occupation has at the national level. We denote the index in this new counterfactual by Γ^*. When comparing Γ and Γ^*, we find that the standard deviation decreases by 20% (15% for the 80 largest MAs and 21% for the 193 smallest MAs).[15] This suggests that differences in the way occupations are paid across the country are more important to explain the different performance of white women across areas than differences in their educational achievements.

Figure 9, which shows the corresponding density functions across the 273 MAs, reveals that most changes occur in the low tail of the distribution (there are almost no changes in the high tail). If there were no spatial differences in the way occupations were valued, there would be barely any MA in which the losses of white women associated with their occupational segregation were above 5% of the national average wage.[16]

(HI) in the case of minority men are areas in which minorities have gains associated with their segregation. In all these areas, except Honolulu, the presence of minorities is low.

[15] The mean of the distribution changes from -0.15 to 0.54.

[16] The spatial dispersion of the relative wage of occupations tends to be higher for occupations having high relative wages. This is the case of aircraft pilots and flight engineers, locomotive engineers and operators, ship engineers, ship captains and operators, life and physical scientists, mathematicians, actuaries and statisticians, architects, lawyers, and judges, inter alia. On the contrary, occupations with low dispersion tend to be those with lower relative wages, as is the case of cooks, food preparation and serving workers, care and service workers, building cleaning workers, home health aides, grounds maintenance workers, clerks, retail sales, secretaries and administrative assistants, material moving workers, and motor vehicle operators.

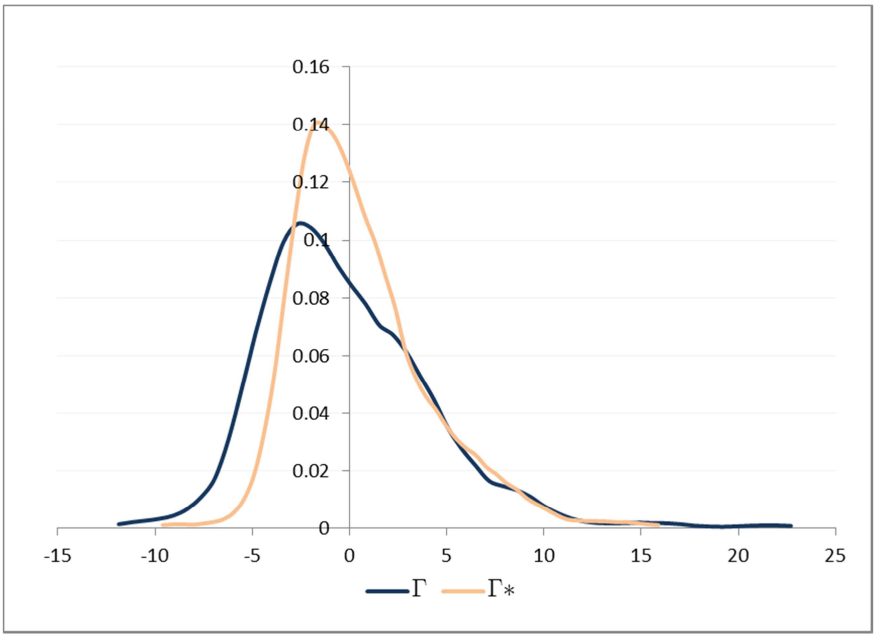


Figure 9. Monetary gains/losses of white women using the real data (Γ) and the wage-counterfactual (Γ^*): Density functions for the 273 MAs, 2007-11

5.4 Spatial Differences in the Industrial Composition of MAs

One may think that the industrial composition of an area might facilitate or halt the integration of white women into the labor market. For this reason, we now explore whether this factor plays any role in explaining the spatial disparities of index Γ across MAs. For this purpose, we build a counterfactual distribution where the share of each sector is the same everywhere and is equal to that at the national level. We consider 12 sectors: Agriculture, Forestry, and Fisheries;[17] Construction; Manufacturing; Transportation, Communications, and other Public Utilities; Wholesale Trade; Retail Trade; Finance, Insurance, and Real Estate; Business and Repair Services; Personal Services; Entertainment and Recreation Services; Professional and Related Services; and Public Administration.[18]

Figure 10 shows that there are almost no differences between the density function of Γ with the observed data and the density function in the counterfactual distribution (once there are no differences in the industrial structure of MAs). In line with this, the standard deviation barely changes (from 4.33 to 4.13, a decrease of less than 5%), which suggests that the industrial

[17] We have added Mining to this sector because it is too small at a MA level to be considered alone.
[18] As mentioned above, we have excluded from our analysis military specific occupations, but there are some persons who work for the army in other occupations. They have been added to the Public Administration category because its too small to be considered independently.

composition barely explains the spatial disparities that we observe in the monetary gains/loss of white women.

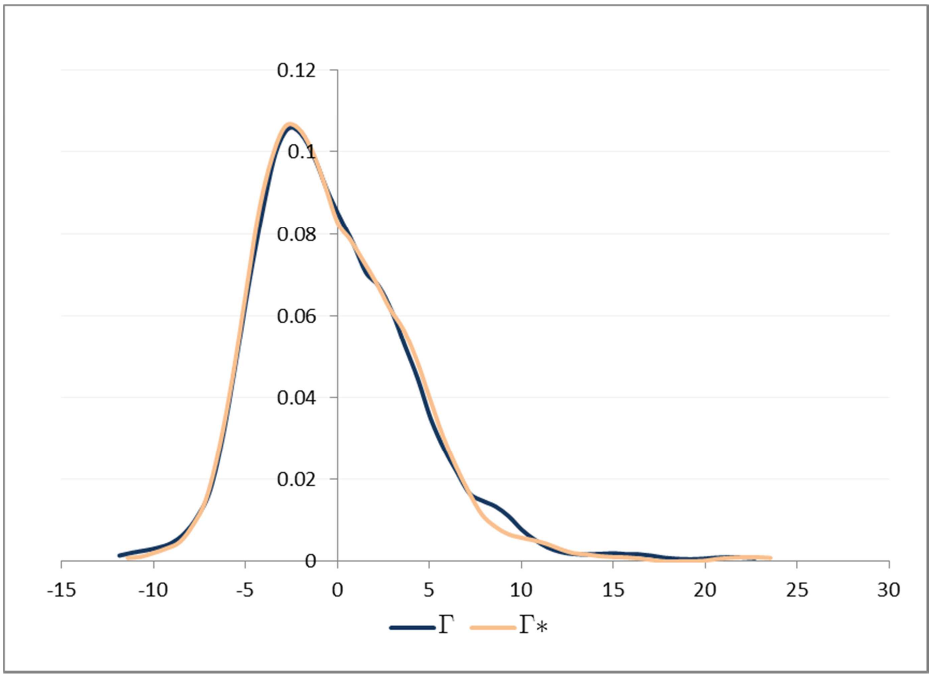


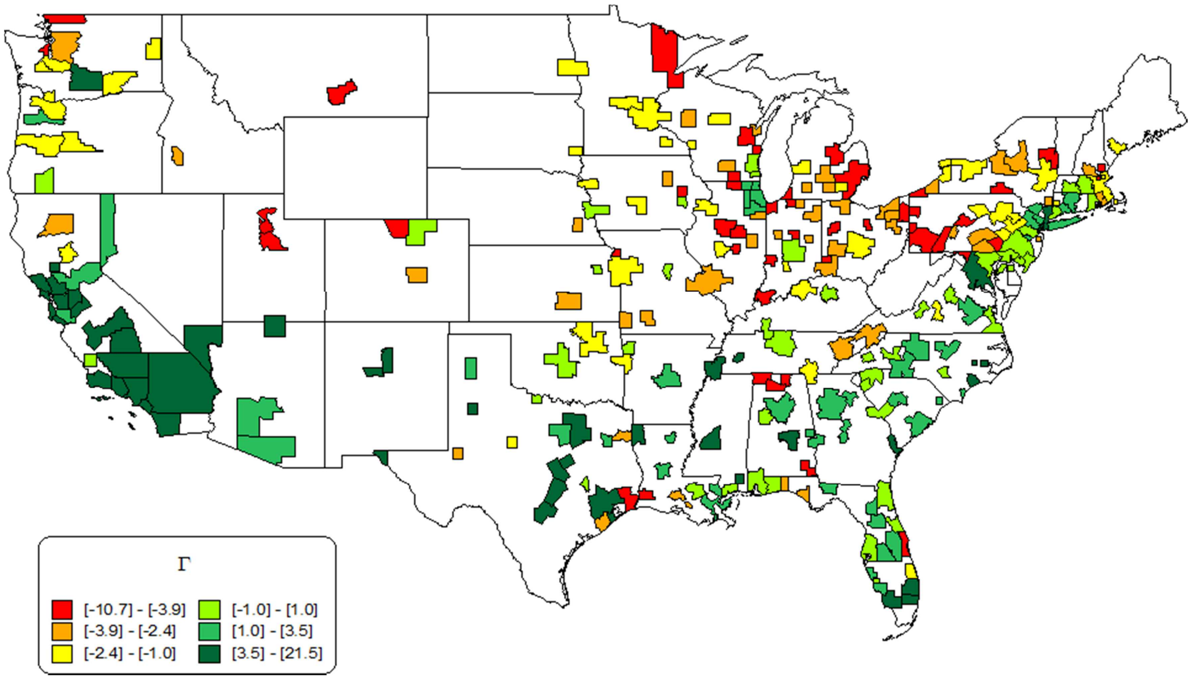
Figure 10. Monetary gains/losses of white women using the real data (Γ) and the industrial structure-counterfactual (Γ^*): Density functions for the 273 MAs, 2007-11

5.5 Spatial Disparities Across and Within States

Map 1, which shows the values of Γ grouped in 6 classes, suggests a geographic pattern.[19] The MAs where white women have higher gains (between 3.5 and 21.5% of the average wage of the area) are mainly in California, Texas, Florida, and North Carolina (and, to a lower extent, Mississippi, New Mexico, Nevada, Arizona, Georgia, South Carolina, and New Jersey). Other areas have values around zero, which means that the occupational sorting of white women is not especially profitable or unprofitable for them.

On the contrary, in many areas in Wisconsin, Michigan, Ohio, Indiana, Utah, and Pennsylvania white women have important losses associated with their occupational sorting, while in Alabama, Illinois, New York, and Washington there are important inner discrepancies.

[19] For scale reasons, Hawaii and Alaska are not shown in the map. The Γ values for Honolulu and Anchorage are 7.6 and 2.6, respectively.



Map 1. Monetary gains/losses of white women in MAs (Γ) grouped into several classes, 2007-11

To explore whether states play a role in explaining the situation of white women, we calculate what share of total discrepancies between areas is due to differences that exist between states and what share is due to differences within states. For that purpose, and taking into account that Γ has both positive and negative values, we use an absolute inequality index, the variance, which can be easily decomposed in these two components:

$$\mathrm{var}(\Gamma) = \underbrace{\sum_{s=1}^{S} \frac{n_s}{N} \mathrm{var}(\Gamma_s)}_{\text{Within component}} + \underbrace{\sum_{s=1}^{S} \frac{n_s}{N} (\bar{\Gamma}_s - \bar{\Gamma})^2}_{\text{Between component}},$$

where n_s is the number of MAs in state s, N is the total number of MAs, $\mathrm{var}(\Gamma)$ is the variance of Γ across MAs, $\mathrm{var}(\Gamma_s)$ is the variance of Γ across areas included in state s, $\bar{\Gamma}$ is the average value of Γ, and $\bar{\Gamma}_s$ is the average value of Γ within state s. The *between* component represents the variance that would exist if all the areas included in a state had the same Γ value, i.e., if there were no differences within states.

When exploring only those states in which there are at least 2 MAs, we find that the *between* component explains around 48% of total disparities among areas, while the *within* component accounts for the remaining 52%. In other words, states seem to play an important role in explaining the spatial pattern of white women's gains/losses.

In our previous analysis, we saw that the race-gender composition of an area was an important factor of the spatial discrepancies of Γ. The question we pose now is whether states still play a role after homogenizing by this variable. For this purpose, we use the *within-between* decomposition of the counterfactual Γ^{*} that we obtained in Section 5.2. In this case, we find that the *between* component reduces to 35%, which suggests that differences between states are partially explained by their demography but also that states play a role beyond it. When homogenizing by the education of white women, we also observe a decrease in the *between* component, although it is not as strong (the *between* component is now 42%).

The same kind of analysis for the counterfactuals by industrial structure and relative wage of occupations reveals, however, that even the *between* component increases (it is 50% and 52%, respectively). Therefore, if we homogenized by each of these variables, the discrepancies among states in the gains/losses of white women would be even higher than those shown before.

5.6 Spatial Disparities Using a Regression Analysis

The counterfactual analyses undertaken so far allowed us to unveil the effects of each single variable on the distribution of Γ across MAs, showing not only the changes to the average and dispersion but also to the shape of the distribution. We now go a step further and explore the joint effect of these variables on the expected value of Γ by carrying out a regression analysis. In doing so, we keep the previous categorization of occupations (94 occupations) and list of areas (273 MAs). Table 2 reports the OLS estimates for various specifications in which the explained variable is Γ.

Whereas in our previous analysis we homogenized by demographic composition, educational structure of white women, wage structure, and industrial structure, we now use several variables that proxy them. Thus, for each MA, we use the proportion of minorities (*% Minorities*); proportion of white women with a bachelor's degree (*% WW with bachelor's degree*); average wage of occupations (*Wages of occupations*); average relative wage, or average status, of occupations standardized by its standard deviation (*Status of occupations*); manufacturing share (*% Manufacturing*), share of business and repair services (*% Business & repair services*), and wholesale trade share (*% Wholesale trade*).[20] Another variable included in the regression analysis is the value of Γ of the state calculated through the average value of

[20] The shares of other sectors turned out not to be statistically significant and thus they are not included here.

the MAs included in that state (Γ-*state*). We also control for the number of workers in millions (*MA size*) and number of workers raised to two (*MA squared*).

Explanatory variables	1	2	3	4	5	6	7
MA size (million)	2.344***	-1.447***	-1.882***	-1.355***	-0.228	0.013	0.196
	(0.850)	(0.493)	(0.469)	(0.449)	(0.483)	(0.506)	(0.492)
MA squared	-0.042	0.435***	0.481***	0.385***	0.136	0.105	0.097
	(0.245)	(0.116)	(0.116)	(0.113)	(0.113)	(0.123)	(0.108)
% Minorities		0.239***	0.229***	0.229***	0.200***	0.192***	0.150***
		(0.016)	(0.017)	(0.016)	(0.014)	(0.015)	(0.020)
% WW with bachelor's degree			0.057**	0.106***	0.219***	0.209***	0.231***
			(0.024)	(0.028)	(0.037)	(0.037)	(0.038)
Wages of occupations				-0.358***	-0.362***	-0.337***	-0.389***
				(0.090)	(0.081)	(0.083)	(0.088)
Status of occupations					1.264***	0.983***	1.012***
					(0.269)	(0.243)	(0.248)
% Manufacturing						-0.087***	-0.061**
						(0.029)	(0.029)
% Business & repair services						-0.427***	-0.440***
						(0.153)	(0.135)
% Wholesale trade						0.638***	0.738***
						(0.177)	(0.188)
Γ - State							0.294***
							(0.072)
Intercept	-1.041***	-6.025***	-7.512***	-2.034	-31.590***	-24.134***	-23.823***
	(0.340)	(0.335)	(0.722)	(1.432)	(6.495)	(5.926)	(5.958)
R^2	0.103	0.685	0.693	0.710	0.746	0.772	0.794
Number of observations	273	273	273	273	273	273	265

Notes: Significance, *10%, **5%, ***1%. Standard errors in parentheses.

Table 2. OLS regression results for assessment of segregation of white women (Γ) across US MAs, 2007-11

The first column in Table 2 shows that the size of the metropolitan labor market has a significant positive effect. However, after controlling for other characteristics, it turns out that this variable is no longer significant. The second specification confirms our previous finding regarding the demographic composition: white women have higher gains associated with their occupational sorting in local markets with larger proportions of minorities, with the coefficient remaining highly significant after controlling for the rest of the variables. The introduction of this variable has an important effect on the R^2, which rises to 0.68. As expected, the proportion of white women with bachelor's degrees also has a positive effect. In subsequent specifications, both the value of this coefficient, which eventually becomes similar to that of *% minorities*, and its significance increase. Therefore, the higher the educational achievements of white women, the larger the gains they get from their occupational sorting.

Even though there is a positive relation between the average wage of occupations and Γ, once we control for the percentage of minorities (and also the percentage of white women with bachelor's degrees), the effect of this variable is significant but negative (specifications 4-7). This suggests that once the percentage of minorities is fixed, white women do not seem to benefit from working in MAs with higher average occupational wages. Note that this variable takes into account the wage of each occupation but not how many people work in it. To account for this, in specification 5 we introduce the average status of occupations, $\sum_j \frac{(w_j/\overline{w})}{94}$, which can be rewritten as the quotient between the average wage of occupations and the average wage of workers.[21] This ratio tends to be higher when the proportion of workers who work in "bad" occupations is relatively large and the proportion of those who work in "good" occupations is relatively low. In other words, it reflects whether the labor structure is one mainly based on relatively low-paid or, on the contrary, relatively high-paid occupations. When introducing this variable in the model, we find that its coefficient is positive and significant and does not change the sign of the variables included so far (although *MA size* and *MA squared* turn out not be significant).[22]

The share of either manufacturing or business & repair services seems to have a negative effect, especially the latter sector. In other words, white women are worse off in metropolitan labor markets with large proportions of these sectors. On the contrary, the share of wholesale trade has a high positive effect. Therefore, although in our counterfactual analysis the whole industrial structure of an area did not seem to explain the spatial disparities in the situation of white women, once we control for other variables, some sectors do seem to play important roles, roles that may be offset by those of other sectors so that the final effect disappears when homogenizing by the industrial structure.

[21] As mentioned above, this variable is actually introduced in the model standardized.

[22] We have estimated another specification, not included in Table 2, that is similar to specification 5 but uses the average wage of workers rather than (average) *wages of occupations* and (average) *status of occupations*. The coefficient of this new variable is significant and negative, which is in line with the effect of *wages of occupations* (the effects of the other variables are similar to those of specification 5). Although this variable is simpler, we choose to keep specification 5 because it allows us to show the different performance between occupations' wages and individuals' wages, which depends on how workers are distributed across occupations. The results of specifications 6 and 7 will also remain the same if we use the average wage of workers rather than the other two variables.

Finally, specification 7 shows that the performance of white women at the state level has a positive effect on their performance at the metropolitan level.[23] In other words, states may be playing a role in the gains/losses of white women associated with their occupational sorting that goes beyond the education of white women, the demographic composition of their labor market, and their industrial and wage structures. This finding confirms our previous analysis. The remaining variables that were significant in previous specifications are also significant now. This means that these variables play a role in explaining not only differences among metropolitan areas belonging to different states but also differences among areas within states.

6. Conclusions

This paper has given evidence on the spatial discrepancies that exists in the occupational sorting of white women and, especially, on the effect that this sorting has on the earning gap of this group. Based on the 2007-2011 sample of the IPUMS and considering 94 occupational titles, our analysis reveals that although segregation brings white women as a whole a per capita estimated gain of 1% of the average wage of the country, in some MAs these women have gains of around 21% of the average wage in the area while in others they instead have losses of 11%. Therefore, an analysis of segregation of white women at the national level seems to mask the real situation of this group. Apart from the disadvantages that white women face in terms of receiving lower wages than their male counterparts working in the same occupation and MA, the occupational distribution of these women remains an issue to deal with in many local labor markets. A total of 49% of white women work in areas in which they have losses associated with their segregation while all their male counterparts work in areas in which they get gains and 50% of them work in areas in which their gains are at least 9%.

Our analysis has also shown that the situation of minority women is much more severe than that of white women since their occupational sorting gives them losses everywhere, including the MAs in which racial minorities account for most of the labor force. Although not the focus of this paper, this highlights the convenience of examining gender-race groups separately because when dealing with women as a whole the plight of minority women can be masked. In taking this perspective, this paper joins an increasing body of literature that calls for the

[23] In this specification, we exclude from the analysis 8 MAs, those that are in states with only one MA in our dataset.

necessity of exploring segregation in a multigroup context rather than just exploring segregation by gender.

This paper has taken a first step to explore the causes of the spatial disparities in the gains/losses of white women associated with their occupational segregation. This investigation suggests that the educational achievements of white women and, especially, the gender-race composition of MAs help explain much of these spatial discrepancies. Our findings appear to be consistent with labor market segmentation and queuing process theories (Reskin and Roos, 1990; Kaufman, 2002). The size of particular sectors—such as wholesale trade, business and repair services, and, to a lesser extent, manufacturing—also seems important. Perhaps differences in collective bargaining agreements, unionization rates, feminization rates, etc., may explain the different performance of sectors. Disparities in the way metropolitan labor markets value occupations play important roles as well. Examining why the relative value of an occupation differs across MAs goes beyond the scope of this paper but it might be related to spatial differences in the gender-race composition of occupations. There is evidence that the reward of an occupation depends on the demographic group that usually fills it. In particular, feminization processes tend to involve devaluation, and this devaluation depends on local labor market factors (Cohen and Huffman, 2003). Future research should explore this issue further.

A first exploration of the geographic variation across MAs reveals that about half of the differences arise from differences across states (the other half comes from differences within states). Differences among states are significant even after controlling for demographic, educational, industrial, and earning variables. Whether this is indicative of particular policies undertaken by the states or the consequences of different social attitudes or ideologies cannot be ascertained here and would require further investigation to determine. Certainly, states undertake many labor regulations, including equal employment opportunities, and are now the main actors in shaping the welfare system—whose programs may involve work requirements—and have an increasing legislative activity on immigration policy. All these factors could affect the situation of white women either directly or indirectly as the labor opportunities that states bring to minority women and men may also affect them.

References

Abrahamson, Mark and Lee Sigelman (1987): "Occupational Sex Segregation in Metropolitan Areas." *American Sociological Review* 52: 588-597.

Albelda, Randy (1986): "Occupational Segregation by Race and Gender, 1958-1981." *Industrial and Labor Relations Review* 39(3): 404-411.

Alonso-Villar, Olga and Coral del Río (2010): "Local versus Overall Segregation Measures." *Mathematical Social Sciences* 60: 30-38.

Alonso-Villar, Olga and Coral Del Río (2013): "The Occupational Segregation of Black Women in the United States: A Look at its Evolution from 1940 to 2010." ECINEQ WP2013-304.

Alonso-Villar, Olga, Coral del Río, and Carlos Gradín (2012): "The Extent of Occupational Segregation in the United States: Differences by Race, Ethnicity, and Gender." *Industrial Relations* 51(2): 179-212.

Alonso-Villar, Olga, Carlos Gradín, and Coral del Río (2013): "Occupational Segregation of Hispanics in U.S. Metropolitan Areas." *Applied Economics* 45 (30): 4298-4307.

Beller, Andrea (1985): "Changes in the Sex Composition of U.S. Occupations, 1960-1981." *Journal of Human Resources* 20: 235-250.

Bianchi, Suzanne and Nancy Rytina (1986): "The Decline of Occupational Sex Segregation during the 1970s: Census and CPS Comparisons." *Demography* 23: 79-86.

Blau, Francine D., Peter Brummund, and Albert Yung-Hsu Liu (2013): "Trends in Occupational Segregation by Gender 1970-2009: Adjusting for the Impact of Changes in the Occupational Coding System." *Demography* 50: 471-492.

Browne, Irene and Joya Misra (2003): "The Intersection of Gender and Race in the Labor Market." *Annual Review of Sociology* 29: 487-513.

Cohen, Philip (2013): "The Persistence of Workplace Gender Segregation in the US." *Sociology Compass* 7/11: 889–899.

Cohen, Philip and Matt Huffman (2003): "Occupational Segregation and the Devaluation of Women's Work across U.S. Labor Markets." *Social Forces* 81(3): 881-908.

Cotter, David, JoAnn DeFiore, Joan M. Hermsen, Brenda Marsteller Kowalewski, and Reeve Vanneman (1997): "All Women Benefit: The Macro-Level Effect of Occupational Integration on Gender Earnings Equality." *American Sociological Review* 62 (5): 714-734.

Cotter, David, Joan Hermsen, and Reeve Vanneman (2003): "The Effects of Occupational Gender Segregation across Race." *The Sociological Quarterly* 44(1): 17-36.

Del Río, Coral and Olga Alonso-Villar (2014): "Local Segregation and Well-being." ECINEQ Working Paper 2014-320.

Del Río Coral and Olga Alonso-Villar (2015): "The Evolution of Occupational Segregation in the U.S., 1940-2010: The Gains and Losses of Gender-Race/Ethnic Groups." *Demography*, forthcoming.

Frankel, David and Oscar Volij (2011): "Measuring School Segregation." *Journal of Economic Theory* 146(1): 1-38.

Gauchat, Gordon, Maura Kelly, and Michael Wallace (2012): "Occupational Gender Segregation, Globalization, and Gender Earnings Inequality in U.S. Metropolitan Areas." *Gender and Society*, forthcoming.

Gradín, Carlos, Coral del Río, and Olga Alonso-Villar (2015): "Occupational Segregation by Race and Ethnicity in the US: Differences across States." *Regional Studies*, forthcoming (DOI:10.1080/00343404.2013.864384).

Hegewisch, Ariane, Hannah Liepmann, Jeffrey Hayes, and Heidi Hartmann (2010): "Separate and Not Equal? Gender Segregation in the Labor Market and the Gender Wage Gap." IWPR Briefing Paper, Washington, D.C..

Hegewisch, Ariane, Claudia Willians, and Amber Henderson (2011): "The Gender Wage Gap by Occupation." IWPR Fact Sheet, Washington, D.C.

Jones Jo and Rachel Rosenfeld (1989): "Women's Occupations and Local Labor Markets: 1950 to 1980." *Social Forces* 67(3): 666-692.

Karmel, Tom and Maureen MacLachlan (1988): "Occupational Sex Segregation—Increasing or Decreasing?" *The Economic Record* 64: 187-195.

Kaufman, Robert (2002): "Assessing Alternative Perspectives on Race and Sex Employment Segregation." *American Sociological Review* 67: 547-572.

King, Mary (1992): "Occupational Segregation by Race and Sex, 1940-88." *Monthly Labor Review* 115: 30-37.

Levanon, Asaf, Paula England, and Paul Allison (2009): "Occupational Feminization and Pay: Assessing Causal Dynamics Using 1950-2000 U.S. Census Data." *Social Forces* 88: 865-981.

Lorence, Jon (1992): "Service Sector Growth and Metropolitan Occupational Sex Segregation." *Work and Occupations* 19: 128-156.

McDaniel, Anne, Thomas A. DiPrete, Claudia Buchmann, and Uri Shwed (2011): "The Black Gender Gap in Educational Attainment: Historical Trends and Racial Comparisons." *Demography* 48: 889-914.

Mintz, Beth and Daniel H. Krymkowski (2011): "The Intersection of Race/Ethnicity and Gender in Occupational Segregation." *International Journal of Sociology* 40(4): 31-58.

Moir, Hazel and Joy Selby Smith (1979): "Industrial Segregation in the Australian Labour Market." *Journal of Industrial Relations* 21: 281-291.

Mouw, Ted and Arne L. Kalleberg (2010): "Occupations and the Structure of Wage Inequality in the United States, 1980s to 2000s." *American Sociological Review* 75(3), 402-431.

Ovadia, Seth (2003): "The Dimensions of Racial Inequality: Occupational and Residential Segregation across Metropolitan Areas in the United States." *City & Community* 2, 313-333.

Perales, Francisco and Sergi Vidal (2013). "Looking Inwards: Towards a Geographically Sensitive Approach to Occupational Sex Segregation." *Regional Studies*, forthcoming

Petersen, Trond and Laurie Morgan (1995): "Separate and Unequal: Occupation-Establishment Sex Segregation and the Gender Wage Gap." *American Journal of Sociology* 101(2), 329-365.

Reid, Lesley, Robert Adelman, and Charles Jaret (2007): "Women, Race, and Ethnicity: Exploring Earnings Differentials in Metropolitan America." *City & Community* 6(2): 137-156.

Reskin, Barbara (1999): "Occupational Segregation by Race and Ethnicity Among Women Workers." In Irene Browne, ed., *Latinas and African American Women at Work. Race, Gender, and Economic Inequality*, pp. 183-204. New York: Russell Sage Foundation.

Reskin, Barbara, Lowell Hargens, and Elizabeth Hirsh (2004): "Picturing Segregation: The Structure of Occupational Segregation by Sex, Race, Ethnicity, and Hispanicity." Unpublished paper, University of Washington.

Reskin, Barbara and Denise Bielby (2005): "A Sociological Perspective on Gender and Career Outcomes." *Journal of Economic Perspectives* 19(1): 71-86.

Reskin, Barbara and Patricia Ross (1990): *Job Queues, Gender Queues: Explaining Women's Inroads into Male Occupations*. Philadelphia: Temple University Press.

Ruggles, Steven, Trent Alexander, Katie Genadek, Ronald Goeken, Matthew Schroeder, and Matthew Sobek (2010): "Integrated Public Use Microdata Series: Version 5.0" [Machine-readable database]. Minneapolis, MN: Minnesota Population Center.

Semyonov, Moshe and Richard Scott (1983): "Industrial Shifts, Female Employment, and Occupational Differentiation: A Dynamic Model for American Cities, 1960-1970." *Demography* 20(2): 163-176.

Semyonov, Moshe, Yitchak Haberfeld, Yinon Cohen, and Noah Lewin-Epstein (2000): "Racial Composition and Occupational Segregation and Inequality across American Cities." *Social Science Research* 29: 175-187.

Silber, Jacques (1992): "Occupational Segregation Indices in the Multidimensional Case: A Note." *The Economic Record* 68: 276-277.

Spriggs, William and Rhonda Williams (1996): "A Logit Decomposition Analysis of Occupational Segregation: Results for the 1970s and 1980s." *Review of Economics and Statistics* 78: 348-355.

Tomaskovic-Devey, Donald, Catherine Zimmer, Kevin Stainback, Corre Robinson, Tiffany Taylor, and Tricia McTague (2006): "Documenting Desegregation: Segregation in American Workplaces by Race, Ethnicity, and Sex, 1966-2003." *American Sociological Review* 71: 565-588.

U.S. Bureau of Labor Statistics (2013): "Hightlights of Women's Earnings in 2012." Report 1045.

Wang, Wendy and Kim Parker (2011): "Women See Value and Benefits of College; Men Lag on Both Fronts, Survey Finds." Pew Research Center, Social and Demographic Trends, available at http://www.pewsocialtrends.org/files/2011/08/Gender-and-higher-ed-FNL-RPT.pdf.

Appendix

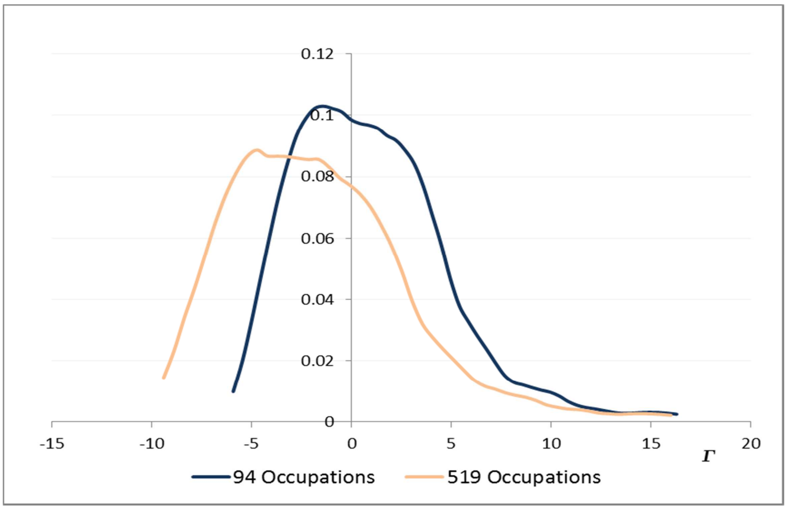


Figure A1. Gains/losses of white women (Γ) in 80 MAs with two occupational classifications: Density functions, 2007-11

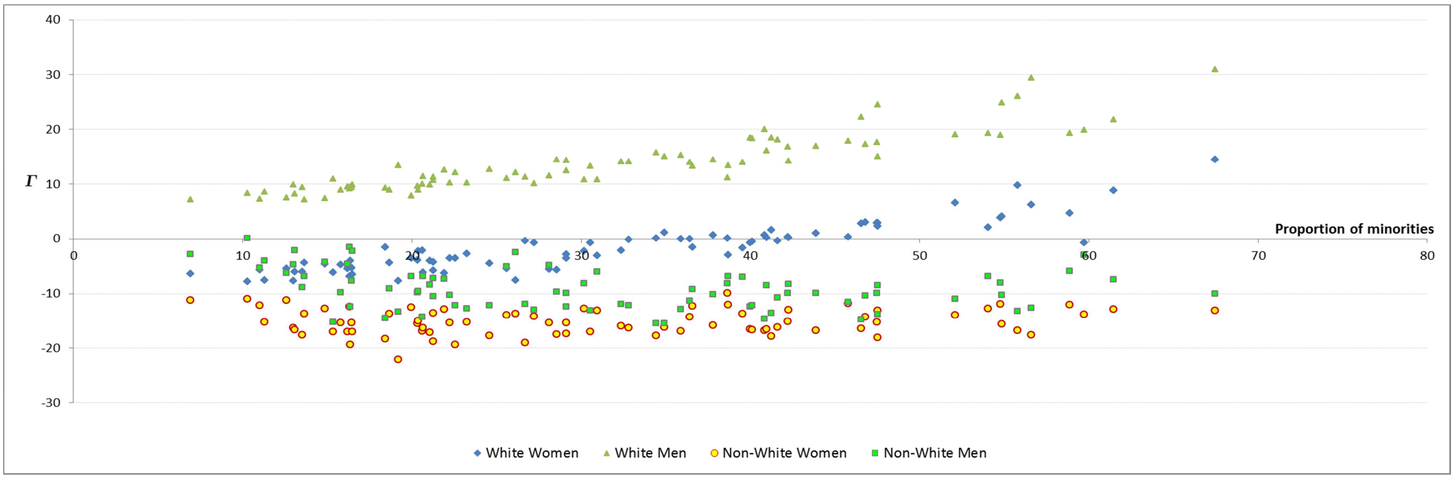


Figure A2. Gains/losses (Γ) of the four gender-race groups: 80 MAs and 519 occupations, 2007-11

Conterfactual Distributions: Some Technical Details

We explain here how to build the counterfactual distribution to homogenize the educational structure of white women across MAs. A similar procedure was also followed to build the counterfactual distribution that homogenizes the race-gender composition of the areas.

We first classify the population (in our case, white women) into mutually exclusive subgroups or "cells" according a certain characteristic (in our case, educational attainment). If *MA* is the categorical variable representing metropolitan area and *z* is the covariate describing the attribute of each cell, the discrete density function of employment of white women across occupations in metropolitan area *l* can be written as:

$$f_l(o) = f(o \mid MA = l) = \int_z f(o \mid z, MA = l) f(z \mid MA = l) dz,$$

where $f(o \mid z, MA = l)$ is the density function corresponding to the distribution across occupations of white women in *l* having attribute *z*, and $f(z \mid MA = l)$ is the attribute density in location *l*. To construct the counterfactual distribution of the above density function, $f_l^*(o)$, we assume that the distribution of white women in each cell across occupations does not depend on the distribution of the attribute (i.e., if $f(o \mid z, MA = l)$ and $f(z \mid MA = l)$ are independent). Then, we keep the observed distribution of white women of a given educational level across occupations unaltered (i.e., $f(o \mid z, MA = l)$), while replacing the density function of the distribution of characteristics in metropolitan area *l* with that of the benchmark (in our case, the entire United States). Therefore, the counterfactual distribution for location *l*

$$f_l^*(o) = \int_z f(o \mid z, MA = l) f(z \mid MA = US) dz$$

represents the occupational distribution that would prevail in metropolitan area *l* if each subgroup of white women kept its own conditional probability of being in a given occupation, but white women in *l* had the same characteristics as in the US in terms of education structure. We proxy $f(z \mid MA = US)$ by the frequency distribution of attributes empirically observed in the US.