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Mapping the Occupational Segregation of White Women in the U.S.: Differences across Metropolitan Areas

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Abstract

This paper investigates the occupational segregation of white women in the U.S. at a metropolitan area level. Our results show substantial variation across areas and suggest that the national scale does not reveal the real situation of white women. The proportion of white women who would have to shift occupations to achieve zero segregation ranges between 20% in some areas and 40% in others. The consequences that occupational segregation has in terms of earnings also vary dramatically within the country, which suggests that in dealing with labor inequalities, local authorities should play an active role.

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1. Introduction

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 (Petersen and Morgan, 1995).

Occupational segregation by gender dropped substantially in the U.S. in the second half of the 20th century but it came to a halt at the beginning of the 21st century (Blau et al., 2013). 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 high degree of masculinization affected five out of ten men (Hegewisch et al., 2011). Women still tend to concentrate in occupations with lower wages, and this occurs even after controlling for education (Del Río and Alonso-Villar, 2015).

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). Likewise, segregation by race/ethnicity does not affect women and men alike (Spriggs and Williams, 1996; Alonso-Villar et al., 2012). 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 special attention should be given to the intersection of gender and race/ethnicity because both contribute to shaping and maintaining inequalities.

The aim of this paper is to investigate the occupational segregation of a particular gender-race group, that of white women, in the U.S. at the metropolitan area level. The U.S. is a racially and ethnically diverse country, which makes it an especially interesting case of study. In this society, 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.

Using the 2007-2011 5-year sample of the Integrated Public Use Microdata Series (IPUMS), this paper estimates, for the first time, the segregation level of white women across metropolitan areas (henceforth, MAs). MAs are considered to be an appropriate unit of analysis for labor patterns (Abrahamson and Sigelman, 1987) and are often referred to as local labor markets (Cotter et al., 2003; Cohen and Huffman, 2003). Our results based on 273 MAs show substantial variation across them. The proportion of white women who would have to shift occupations to achieve zero segregation ranges between 20% and 40%. This result, in line with the spatial variation in segregation by gender shown for other developed countries (Perales and Vidal, 2013), suggests that to deal with occupational segregation, local authorities, and not only national governments, should play active roles. Our results suggest that effective policies aimed at reducing gender/race inequalities should consider the specificities of the local labor market in which they operate. The mix of jobs available to workers in a local labor market, the size of minorities who work there, or the concern that local institutions have for gender/race equality may affect the opportunities that demographic groups actually face. National policies do not seem effective enough to reduce gender and race inequalities.

By examining the segregation of white women at the MA 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 (Reskin, 1999).

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; Perales and Vidal, 2013; Gradín et al., 2015), despite the fact that the situation of a group may depend on the characteristics of the local labor market in which it works (Cohen and Huffman, 2003; Cotter et al., 2003). In fact, variability in segregation by gender seems to be more intense across MAs than nationally across time (Lorence, 1992). It therefore seems convenient to explore whether segregation at the national level reflects the real experience of white women. Moreover, the MA-level analysis allows delving deeper into the

[1] The educational level of white women is, however, lower than that of Asian women (Wang and Parker, 2011).

segregation phenomenon by exploring the causes of its spatial variability, as we do by means of counterfactual and econometric analyses.

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.

Forth, 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 derived from its segregation (Alonso-Villar and Del Río, 2015; Del Río and Alonso-Villar, 2015), and they have done so at the national level. Therefore, no disparities among MAs 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 MA level are scarce (Cotter et al., 2003). This paper extends that literature by quantifying for each MA the earning gap of white women that is derived from their occupational segregation.

The paper is structured as follows. Section 2 introduces the methodology while Section 3 explores the extent and consequences of segregation for white women across MAs. Section 4 goes one step further by attempting to explain the disparities across areas. After presenting the main theories on occupational segregation, this section undertakes counterfactual and regression analyses. Finally, Section 5 offers the main conclusions.

2. Methodology

The index of dissimilarity (Duncan and Duncan, 1955) has been extensively used to quantify the discrepancy between the distribution of women and men across occupations. It has also been used to calculate the segregation between white women and other groups but, by doing so, one does 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, this paper calculates the segregation of white women by comparing its occupational sorting with the occupational structure of the economy (Alonso-Villar and Del Río, 2010; Moir and Shelby Smith, 1979). 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. The price to pay is that this analysis does not inform about the situation of white women against each specific group.

To calculate the segregation of white women in each MA, we use two measures:

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

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

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. 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 MAs. 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 derived from an entropy measure—the Theil index—and takes into account distributive value judgments that are in line with those conducted in the literature on income distribution. Thus, 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* ranges from 0 to 1.[2] An advantage of this index, not unveiled so far, is that it permits a clear economic interpretation. As shown in the Appendix, *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).

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, we use two different measures recently proposed in the literature:

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

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

where w_j is the (average) wage of occupation *j* and $\bar{w} = \sum_j \frac{t_j}{T} w_j$ 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 (Alonso-Villar and Del Río, 2015). The second index measures the *per capita* monetary gain or loss of white women derived from their segregation (Del Río and Alonso-Villar, 2015).[3] 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, as we discuss below.

[2] In a dichotomous context, *D* is consistent with the index of dissimilarity. Thus, in the case of segregation by gender, the index of dissimilarity 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). *D* is also consistent with the multigroup index developed by Silber (1992), see Alonso-Villar and Del Río (2010).

[3] Ψ represents a *well-being* loss/gain due to the concavity of function *ln*, which makes the index show inequality aversion. Γ shows instead inequality neutrality.

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.

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 while for index Γ both advances are equally good if they involve monetary gains of the same magnitude (in our example, a \$100 increase). In addition, according to Ψ, 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, for Ψ small improvements for many white women are more important than large improvements for only a few. However, for Γ both situations are equally good because the monetary gains are the same in both cases.

In our analysis we use both measures to assess the occupational sorting of white women. 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.

3. The Extent and Consequences of Segregation

The occupational segregation of white women 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, which was also shared by women from other races, did not allow them 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. In 2010, white women still had monetary losses associated with their occupational sorting at the national level, although they were relatively small.

In what follows, we explore the extent and nature of segregation at a MA level, which will allow us to show that working with data at the national level obscures the real experience of white women.

3.1 Dataset

We use the 5-year 2007-2011 sample drawn from the 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).[4] In order to have reliable results, the analysis based on the 519 titles is undertaken only for the 80 MAs where employed 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 MAs because using a similar criterion we find 273 areas (those with at least 940 white female observations).[5] The definition of MA 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] The occupation "military specific occupations" is not included in our analysis.

[5] These thresholds prevent the small-unit bias problem that leads to overestimation of the segregation level of white women in MAs with small samples. Note, however, that dropping MAs do not affect the segregation measurement of the remaining MAs.

[6] 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

3.2 Selected Metropolitan Areas with Detailed Occupational Titles

It is worth noting that the segregation measurement depends on the level of aggregation of occupations. The finer the classification of occupations, the more precise the estimation of segregation is. For this reason, we start our analysis using a classification that consists of 519 occupational titles. To have reliable results we restrict the analysis to 80 large MAs.[7] Therefore, in this section, the measurement of the phenomena is more accurate than in subsequent sections, although the results only apply to these large MAs.

Table 1 shows the segregation level of white women in each of these 80 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).

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 MA level is not too different. 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. Despite the differences between D and Φ, the correlation between them 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 them having a *per capita* loss close to zero at the national level ($\Gamma = -1.6$), some MAs have a much more negative value and others have high positive values. 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 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%. The differences among MAs according to index Ψ are also intense. The correlation between Ψ and Γ is 0.99, which suggests that our results are quite robust against the index used.

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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 two large MAs for which we do not have figures in the dataset (Denver and Miami).

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, 2007-2011

	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

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. In some MAs, the segregation of white women makes them an advantaged group, while in others it causes them a disadvantage.

3.3 Segregation at a MA Level with a Broad Occupational Classification

To have a wider geographic view of the segregation faced by white women, it seems convenient to enlarge the list of MAs considered in the analysis. This requires reducing the occupational titles to avoid biased values in our indexes derived from small samples of white women in some areas. Our list, 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 (Table 1). We see that 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. This means that when we use 94 occupations, the losses of white women associated with their segregation are underestimated. 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).

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 to study 273 MAs, which account for 73% of white women workers.

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. 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 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).

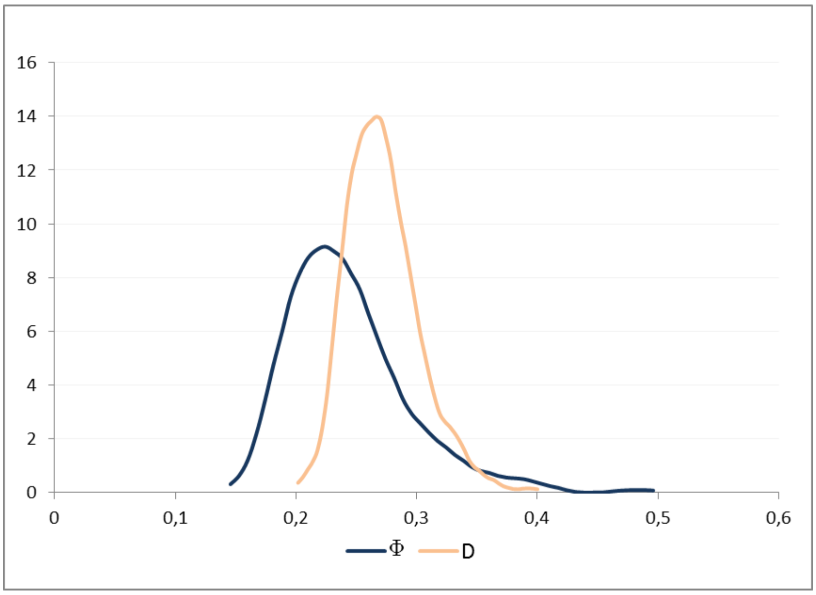


Figure 1. Segregation levels of white women across 273 MAs (indexes Φ and *D*): Density functions, 2007-11

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*).

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).[8] The combination of both occupational sorting disadvantages and within-occupation wage disadvantages makes white women have a positive earning advantage only in a few MAs

[8] The value of Γ at the national level when using 94 titles is 1; see Table 1.

(e.g., Los Angeles, New York, San Antonio, San Francisco, Oakland, and Houston, see Table 1). In most MAs the *EGap* is negative (e.g. Boston, Philadelphia, Chicago, and Seattle).

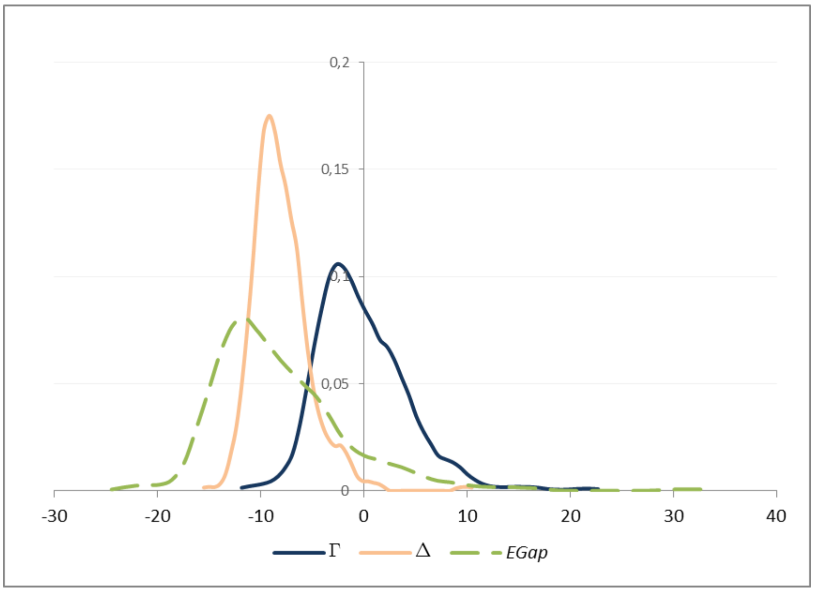


Figure 2. Total earning gap of white women (*EGap*) across 273 MAs and its components (Γ and Δ): Density functions, 2007-11

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.

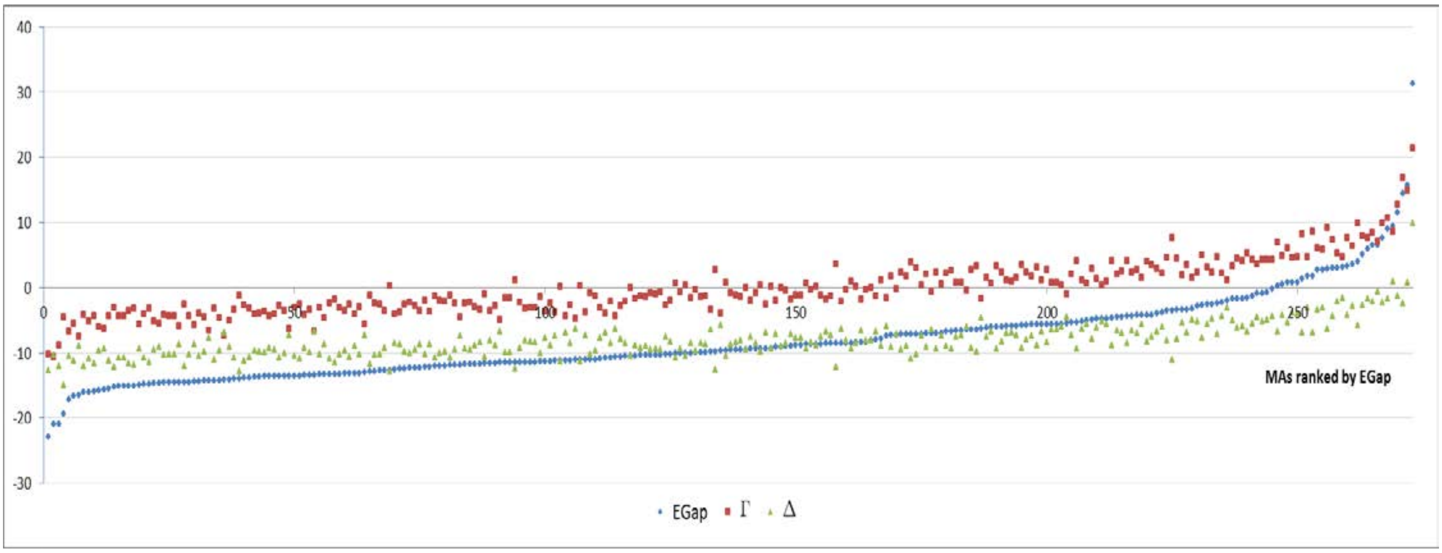


Figure 3. Total earning gap (*EGap*) of white women in each MA and its decomposition in segregation disadvantage (Γ) and within-occupation wage disadvantage (Δ); MAs ranked by their *EGap*: 273 MAs, 2007-11

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.

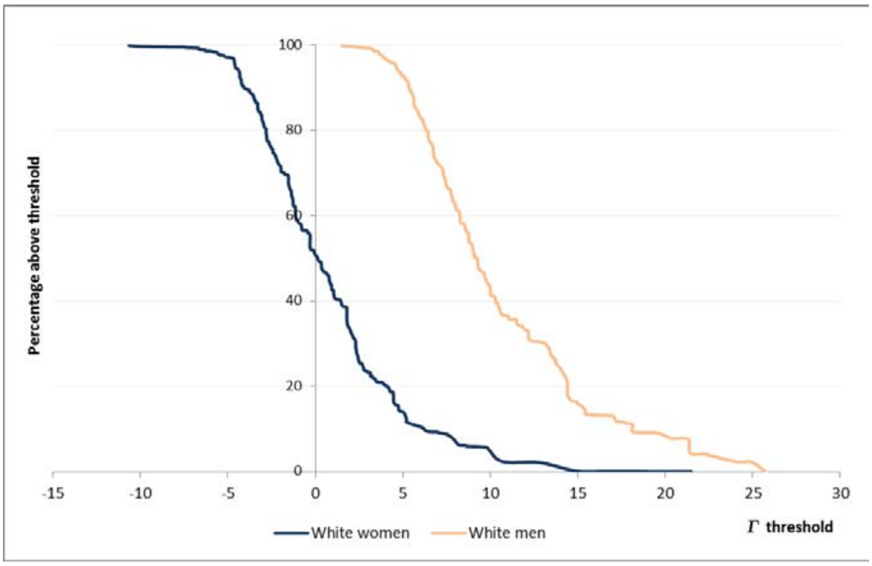


Figure 4. Percentage of white women (or alternatively, white men) working in MAs where Γ is above each threshold, 2007-11

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%.

4. 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 these spatial disparities.

4.1 Theoretical Framework

As opposed to what happens in other economic fields in which locations are interlocked so that what happens in a location is influenced by what happens in nearby locations, no theory has yet been developed to explain the spatial dimension of our phenomenon. The literature on occupational segregation, however, puts on the table a set of factors that can help us understand why the losses/gains of white women are much more intense in some MAs than in others. Some of these approaches emphasize the role played by supply-side factors and sustain that it is the characteristics that workers bring to the labor market that cause their segregation. Thus, the *human capital* approach, which is one of the most widely mentioned, sees job differences among demographic groups as the result of differences in workers' education, experience, and skills. This approach seems to explain part of the occupational segregation existing in American society (Ovadia, 2003; Gradín et al., 2015). Another argument often used is that groups differ in terms of preferences for jobs, although this justification has been given to explain segregation by gender, not race (Kaufman, 2002).

Other approaches underline instead the role played by demand-side factors, i.e., the characteristics of the setting in which work occurs.[9] Some of them claim that the position of women and racial minorities in the labor market is the result of discrimination arising either because employers/workers/consumers have a taste for discrimination or because employers categorize individuals based on the average characteristics of the group to which they belong (statistical discrimination). These discrimination practices against women/minorities can be used by employers to create a secondary labor market in which these workers have lower rewards, status, and employment opportunities (Reskin and Roos, 1990). Stratification is reinforced by queuing labor processes that rank applicants to a job not only by their skills but also by their gender and race/ethnicity (Kaufman, 2002). Social closure theories claim that employers not only penalize some groups but also privilege others with which they have more ties (white males).

It is important to keep in mind that market and organizational structures, personnel practices, and, in general, the social and economic context influences the position of groups in the labor market. Thus, there is evidence that occupational segregation between blacks and whites depends on the size of the Hispanic population (Ovadia, 2003). Therefore, the ranking of a group in the labor queue may depend on the *sizes of other groups*. On the other hand, labor queues and market segmentation may be affected by culture and citizen ideology since more traditional areas usually restrict the access of women/minorities to certain kind of jobs.

[9] Other perspectives combine demand- and supply-side factors, as is the case of the spatial mismatch approach. The mismatch between housing and business location does not seem, however, an important factor to explain the segregation of white women although it could help to explain the segregation of other women.

Population size may also affect white women because larger areas tend to be "more tolerant of diversity in political, sexual, and other life-style choices" (Abrahamson and Sigelman, 1987, pp. 589). Areas also vary in the way occupations are rewarded because this *reward* is influenced by the demographic group that tends to fill each occupation and by characteristics of the local labor market. Thus, in more segregated markets, the devaluation of feminized jobs tends to be more intense (Cohen and Huffman, 2003). Spatial disparities also arise from differences in institutions. *States* with more egalitarian institutional environments tend to exhibit less inequality by race/gender in terms of both earnings and access to good jobs (Beggs, 1995; Ryu, 2010).

The economic context is important as well. Abrahamson and Sigelman (1987) suggest that the higher the percentage of women in the labor force, the lower the segregation by gender. The *industrial structure* of an area may also influence occupational segregation because it affects the mix of jobs available to workers, causing occupations traditionally dominated by women/minorities to be larger/smaller (Abrahamson and Sigelman, 1987; Lorence, 1992). The consequence of this is not s clear, however. For example, areas with a large public administration may enhance female employment due to their family-friendly policies but, at the same time, they may provide a setting for lower-paid occupations because this sector usually yields lower wages (Ryu, 2010).

In exploring the spatial disparities in the gains/losses of white women associated with their occupational sorting, we deal with both supply-side and demand-side sources. First, we account for disparities in the educational achievements of white women, given that education is considered to be an important component of occupational segregation. Second, we take into account the industrial composition of the area to control for the structural propensity to segregate. Third, given that the economic consequences of segregation depend not only on how the group is distributed across occupations but also how occupations are rewarded, we explore the effect of spatial discrepancies in the way occupations are paid. Forth, we account for the size of different gender-race/ethnicity groups because the position of white women may depend on the size of minority groups, and minorities are not homogenously distributed across the country. Fifth, to account for spatial discrepancies on institutions and culture, we explore whether states play a role in the opportunities afforded to white women.

In what follows, we first undertake counterfactual analyses so that we can determine how the shape of the distribution of index Γ across the 273 MAs changes when homogenizing by each of these variables separately. Second, we explore the joint effect of these variables on the expected value of Γ by carrying out an OLS regression analysis as well as two spatial autoregressive models.

4.2 Spatial Differences in the Education of White Women

Spatial differences in the occupational segregation of white women may arise from differences in education, either because white women in some areas invest more on education or the highly educated are attracted to those areas. We distinguish four educational levels (less than a high school diploma, a high school diploma, some college, and a bachelor's degree).

We recalculate index Γ for each MA using a counterfactual distribution, which 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%. 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.[10] We show the analyses for large and small MAs separately because their patterns with respect to education are rather different.

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

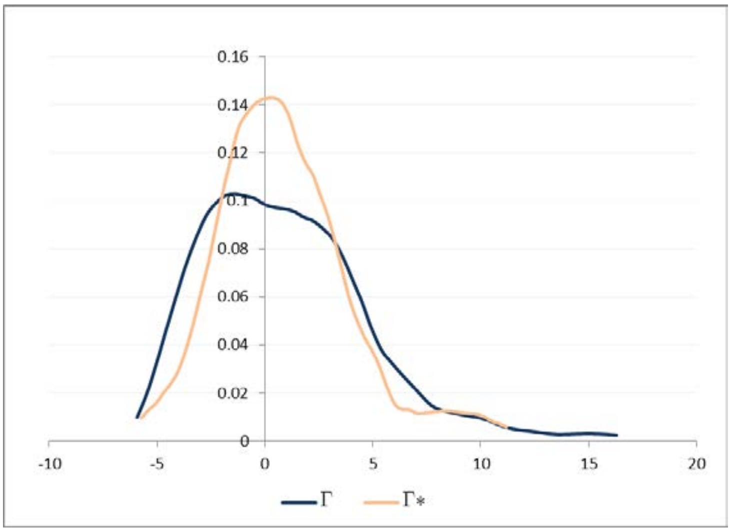


Figure 5. Monetary gains/losses of white women using the real data (Γ) and the education-counterfactual (Γ^*): Density functions for the 80 largest MAs, 2007-11

Figure 5 shows that when we homogenize large MAs by education, the gains/losses of white women decrease. The standard deviation 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.

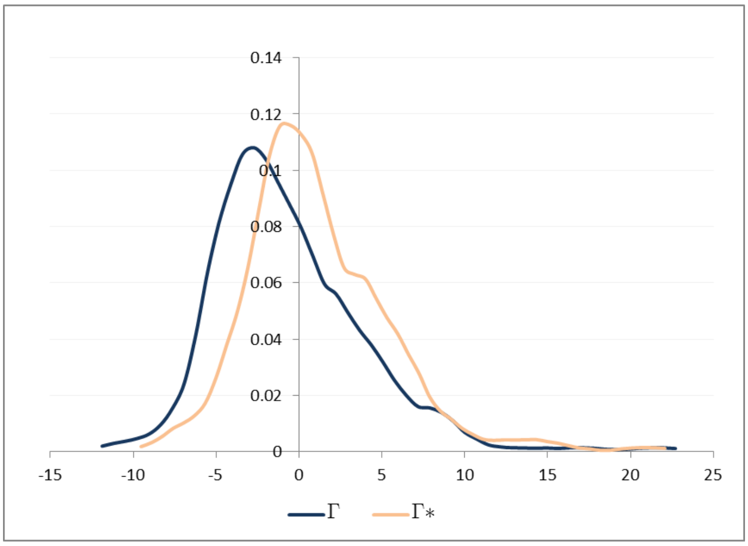


Figure 6. Monetary gains/losses of white women using the real data (Γ) and the education-counterfactual (Γ^*): Density functions for the 193 smallest MAs, 2007-11

The pattern for smaller MAs is quite different. The standard deviation in this case decreases by only 6%. Figure 6 reveals 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, when the proportions of the highly educated group increase, the gains of white women as a whole also increase. In any case, 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.

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

The performance of white may also depend on the representation of other groups and on how the market ranks them (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 reduced by around 35%. 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.

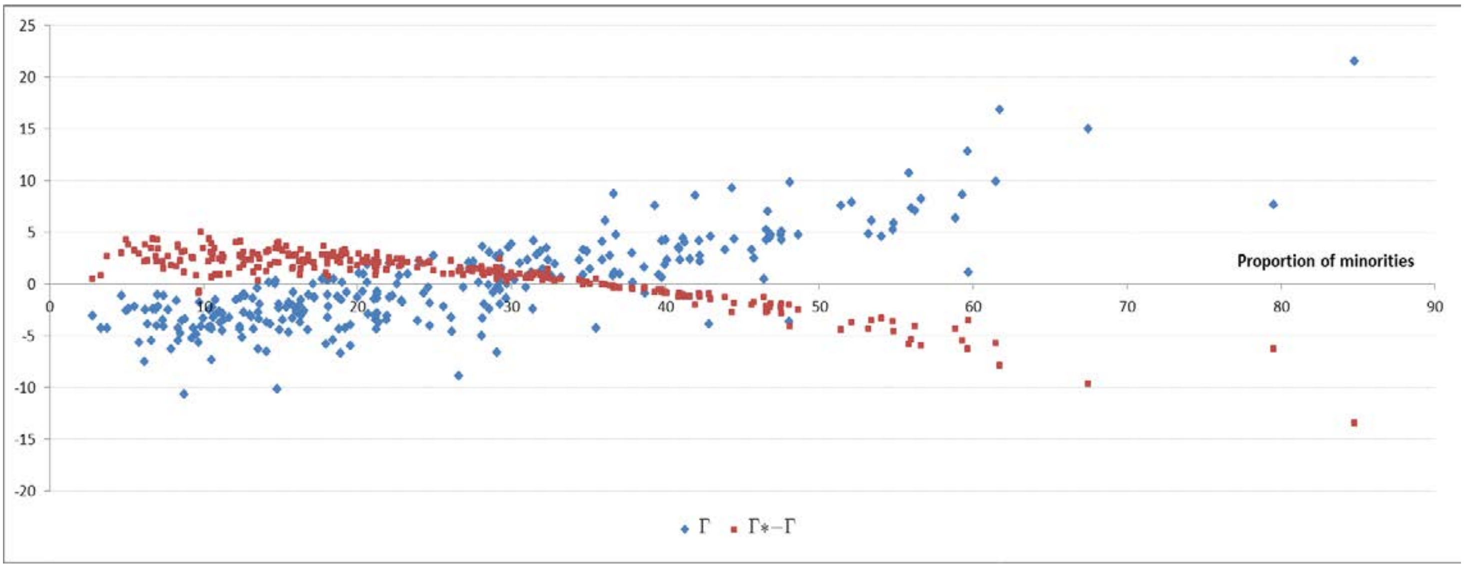


Figure 7. Gains/losses of white women using the real data (Γ) and their differences with respect to the gender-race-counterfactual ($\Gamma^* - \Gamma$): 273 MAs ranked by their minority share, 2007-11

Figure 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 ($\Gamma^* - \Gamma < 0$).

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. White women start to have advantages when the proportion of minority workers in the MA is about 20%. Below that level, only white men tend to have advantages associated with their occupational sorting.

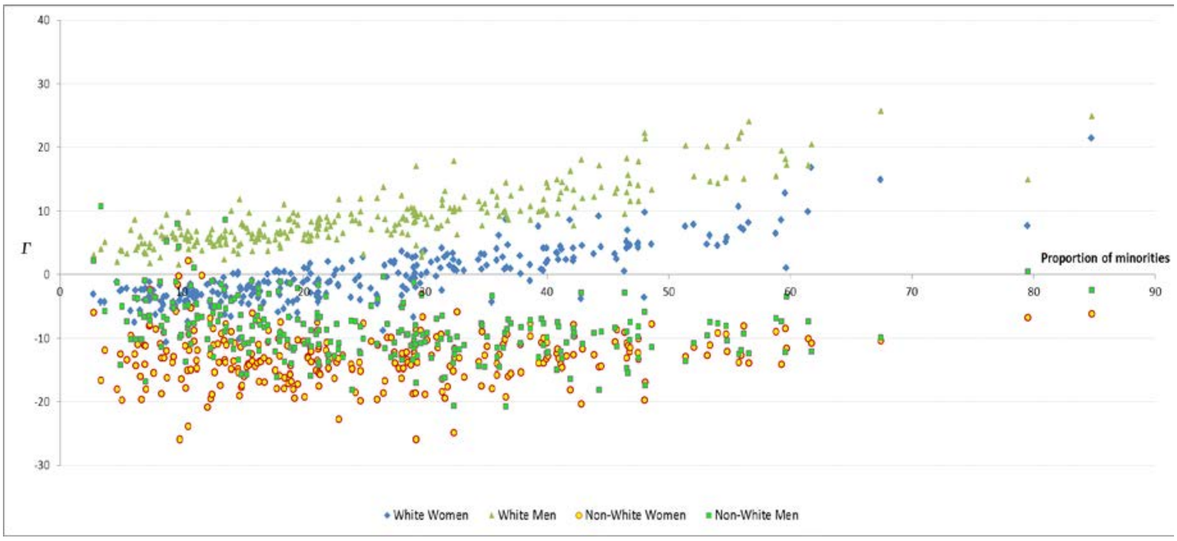


Figure 8. Gains/losses (Γ) of the four gender-race groups: 273 MAs ranked by their minority share, 2007-11

This finding is consistent with theories of labor market segmentation and the queuing process mentioned above (Reskin and Roos, 1990; Kaufman, 2002). 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.

4.4 Spatial Differences in the Relative Pay of Occupations

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%. 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.

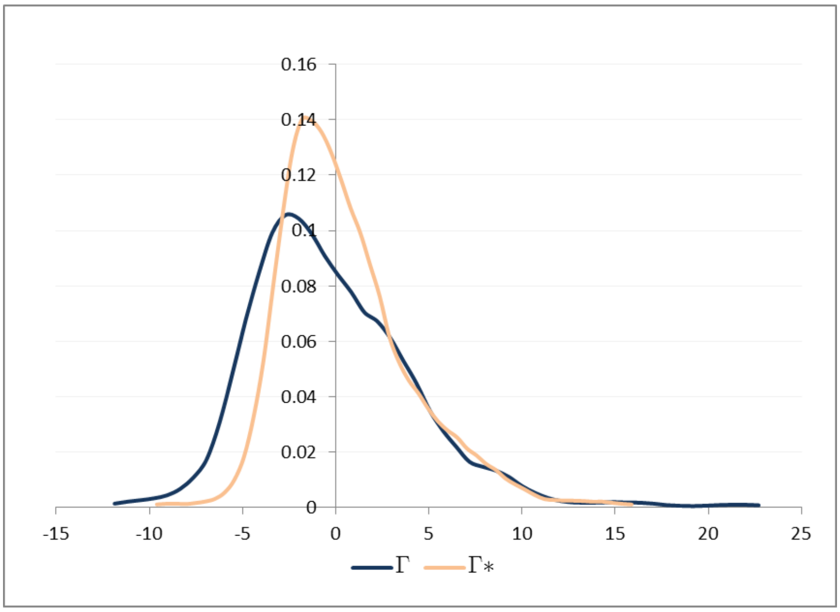


Figure 9. Monetary gains/losses of white women using the real data (Γ) and the wage-counterfactual (Γ^*): Density functions for the 273 MAs, 2007-11

Figure 9, which shows the corresponding density functions across the 273 MAs, reveals that most changes occur in the low tail of the distribution. 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.[11]

4.5 Spatial Differences in the Industrial Composition of MAs

We now explore whether the industrial composition plays any role in explaining the spatial disparities of index Γ across MAs. 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; 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.

[11] The spatial dispersion of the relative wage of occupations tends to be higher for occupations having high relative wages.

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). The standard deviation decreases by only 5%, which suggests that the industrial composition barely explains the spatial disparities that we observe in the monetary gains/loss of white women.

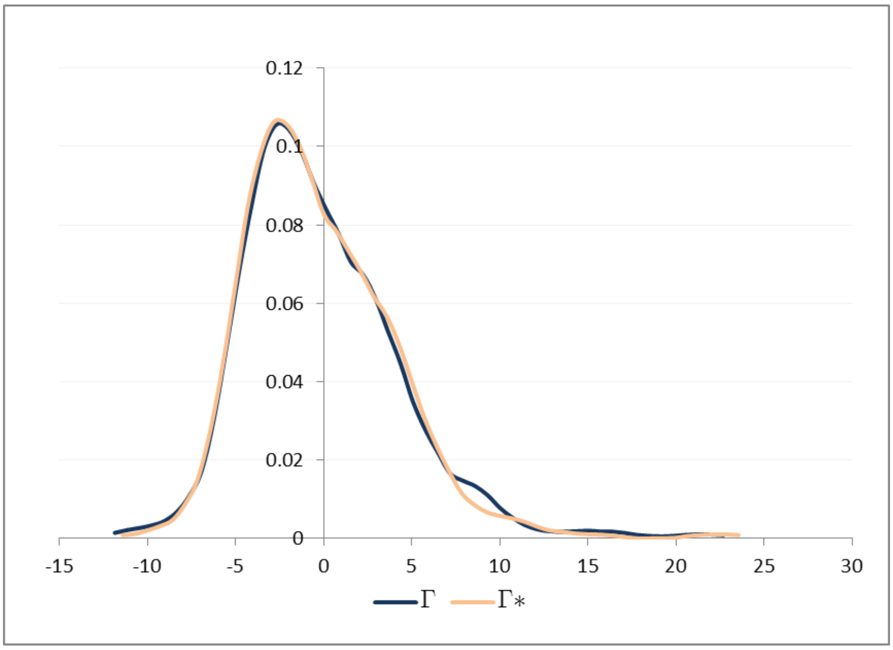
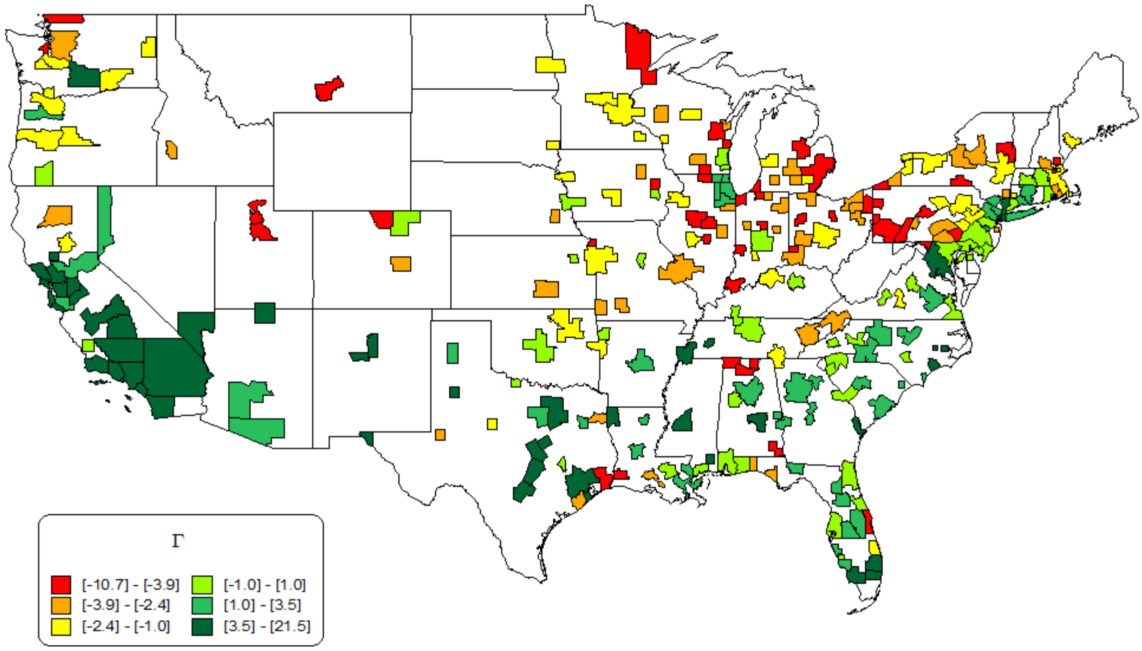


Figure 10. Monetary gains/losses of white women using the real data (Γ) and the industrial structure-counterfactual (Γ^*): Density functions for the 273 MAs, 2007-11

4.6 Spatial Disparities Across and Within States

Map 1, which shows the values of Γ grouped in 6 classes, suggests a geographic pattern.[12] The MAs where white women have higher gains 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). 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.

[12] 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:

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

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*, $\overline{\Gamma}$ is the average value of Γ, and $\overline{\Gamma}_s$ 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.

4.7 Spatial Disparities Using a Regression Analysis

To explore the joint effect of the above variables on the expected value of Γ, we first carry out an OLS regression analysis. Table 2 reports the estimates for various specifications in which the explained variable is Γ. Its purpose is to show the robustness of our results when adding new explanatory variables in the model. The gains of white women are expected to depend positively on the proportion of white women with bachelor's degrees (*% WW with bachelor's degree*), on the proportion of minorities (*% Minorities*), and on the proportion of employees who are women (*Feminization rate*). Since Γ depends on how occupations are rewarded, we control for the average wage of occupations (*Wages of occupations*) and average relative wage of occupations standardized by its standard deviation across MAs (*Relative wages of occupations*). The signs of these variables cannot be determined a priori because they depend on how white women are ranked as compared to other groups. We also control for the industrial structure, although the effect of each sector cannot be inferred from the existing literature. Table 2 only includes the share of business and repair services (*% Business & repair services*), and wholesale trade share (*% Wholesale trade*) because the shares of other sectors turned out not to be statistically significant. Another variable included in the regression analysis is the value of Γ of the state calculated through the average value of the MAs included in that state (Γ*-state*), which is expected to have a positive effect. We also control for the number of workers in millions (*MA size*) because, as mentioned above, the opportunities of white women are expected to increase in larger areas. The number of workers raised to two (*MA squared*) is also included to check whether the above effect reaches a certain threshold.

Table2. Explaining the assessment of segregation of white women across MAs (Γ): OLS regressions (1-7), spatial lag model (8), and spatial error model (9)

Explanatory variables	1	2	3	4	5	6	7	8	9
MA size (million)	2.344***	-1.447***	-1.882***	----	----	----	----	----	----
	(0.850)	(0.493)	(0.469)						
MA squared	-0.042	0.435***	0.481***	0.082	0.085	0.096	0.143***	0.144**	0.137**
	(0.245)	(0.116)	(0.116)	(0.077)	(0.057)	(0.060)	(0.051)	(0.058)	(0.057)
% Minorities		0.239***	0.229***	0.225***	0.199***	0.213***	0. 164***	0. 162***	0. 172***
		(0.016)	(0.017)	(0.016)	(0.013)	(0.013)	(0.018)	(0.015)	(0.016)
% WW with bachelor's degree			0.057**	0.099***	0.220***	0.217***	0.229***	0.231***	0.236***
			(0.024)	(0.028)	(0.036)	(0.034)	(0.034)	(0.027)	(0.027)
Wages of occupations (average)				-0.403***	-0.369***	-0.372***	-0.413***	-0.428***	-0.494***
				(0.090)	(0.080)	(0.078)	(0.083)	(0.076)	(0.092)
Relative wages of occupations (average)					1.289***	1.034***	1.019***	1.001***	0.996***
					(0.249)	(0.230)	(0.229)	(0.186)	(0.188)
% Business & Repair services						-0.300**	-0.301**	-0.322**	-0.326**
						(0.145)	(0.130)	(0.126)	(0.128)
% Wholesale trade						0.611***	0.750***	0.752***	0.735***
						(0.177)	(0.187)	(0.158)	(0.156)
Feminization rate						0.214**	0.232***	0.245***	0.211***
						(0.082)	(0.081)	(0.066)	(0.066)
Γ - State							0.330***	0.269***	0.291***
							(0.069)	(0.085)	(0.071)
Intercept	-1.041***	-6.025***	-7.511***	-1.154***	-32.036***	-37.191***	-36.415***	-36.200***	-33.469***
	(0.340)	(0.335)	(0.722)	(1.452)	(6.169)	(6.994)	(6.917)	(5.611)	(5.830)
Lambda								0.194	
								(0.185)	
Rho									0.752***
									(0.208)
Adjusted R^2	0.097	0.681	0.688	0.700	0.741	0.764	0.792		
Log-Likelihood							-552.095	-551.549	-549.068
Number of observations	273	273	273	273	273	273	265	265	265

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

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, the losses/gains of white women do not seem to depend on the size of the MA. This variable first switches sign and later becomes insignificant, perhaps due to multicollinearity issues. In fact, the variance inflation factor (VIF) of *MA size* increases as one includes additional variables gradually (this is why we do not include it from specification 4 onwards).

The second specification confirms our previous finding regarding demographic composition: white women have higher gains associated with their occupational sorting in MAs 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 adjusted R^2, which rises to 0.681. 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 and its significance increase.

Although the Pearson's correlation coefficient between the average wage of occupations and Γ is positive, once we control for the percentage of minorities (and also the percentage of white women with bachelor's degrees), the effect of *Wages of occupations* is significant but negative. 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 relative wage of occupations, $\sum_j \frac{\left(w_j/\overline{w}\right)}{94}$, which can be rewritten as the quotient between the average wage of occupations and the average wage of workers.[13] 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.

The share of business and repair services has a negative effect. In other words, white women are worse off in metropolitan labor markets with large proportions of this sector. On the contrary, the share of wholesale trade has a high positive effect. Therefore, although in our

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

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. The feminization rate coefficient is significant and positive, which suggests that, once we control for minority size, the MAs with high feminization rates are particularly good for white women in terms of segregation.

Specification 7 (our "best" OLS model) shows that the performance of white women at the state level has a positive effect on their performance at the metropolitan level.[14] This could be due to some state policies or statewide factors. 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 the labor market, the industrial and wage structures, and the feminization rate of MAs. On the other hand, these variables play a role in explaining not only differences among metropolitan areas belonging to different states, as shown in previous specifications, but also differences among areas within states. Apart from these variables, *MA squared* now becomes significant, which shows the positive effect that working in the largest MAs of a state has on white women.

To check whether our results would remain unaltered using a spatial econometric approach, we estimate two spatial autoregressive models, a spatial lag model (model 8), in which the phenomenon is seen as a substantive spatial process, and a spatial error model (model 9), which implies that the scope of the phenomenon goes beyond the unit of analysis. For this purpose, we use a row-standardized inverse-distance matrix based on the Haversine distance between pairs of MAs (using their latitudes and altitudes). The analysis undertaken when including the variables listed in specification 7 in the spatial lag model, estimated by maximum likelihood, reveals that the coefficient associated with the spatial lag of the dependent variable is insignificant. This suggests that the gains/losses of white women in a MA are not affected by their gains/losses in nearby areas. However, the estimation of the spatial error model reveals that the spatial error term is significant. Moreover, this is our "best" model, as implied by the robust Lagrange Multiplier test for spatial error dependence based on the residuals of model 7 and also the Likelihood Ratio test of the spatial error model versus this OLS model.

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

Note, however, that in specification 9, we find almost no changes in the values of the coefficients of the variables listed in specification 7 and their significance. This suggests that the significant variables of our "best" OLS model are also significant when controlling for spatial dependence, although there may exist variables not included in that model whose effects may go beyond the MA. This could be the case of social attitudes or ideologies, which are likely to exceed the MA (and the state) level. A positive spatial correlation in this kind of variable could explain why we find the spatial error term to be significant.

5 Conclusions

A priori one could think that white women are a group with a similar degree of integration in labor markets all over the country. Our analysis reveals, however, that this is not the case. In some MAs segregation brings white women a *per capita* gain of around 21% of the average wage in the area while in others it causes instead a loss of 11% (the loss is close to zero at the national level). 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. Moreover, policies aimed at reducing labor inequalities by gender and race should be channeled not only at the national level but also by subnational authorities. A total of 49% of white women work in MAs 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%. The situation of minority women is much more severe than that of white women since their occupational sorting gives them losses everywhere.

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 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 and business & repair services—also seems important. Perhaps differences in collective bargaining agreements, unionization 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 while the other half comes from differences within states, which suggests that both states and local authorities could play a more active role in reducing employment inequalities. Differences among states are significant even after controlling for demographic, educational, industrial, and earning variables. Whether this is indicative of particular employment 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.

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Appendix

Interpretation of index D

This proof follows the same steps as Karmel and MacLachlan (1988) took for interpreting their modified version of the index of dissimilarity.

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 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.