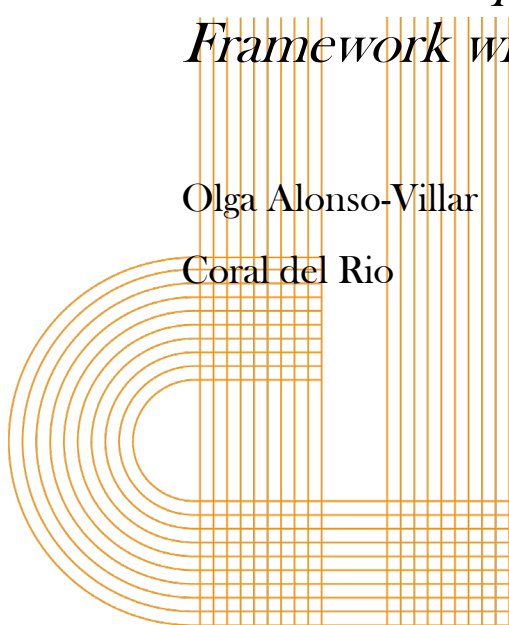


*Privilege and Hindrance on the U.S. Earnings
Distribution by Gender and Race/Ethnicity: The
Role of Occupations in an Intersectional
Framework with 12 Groups*

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Privilege and Hindrance on the U.S. Earnings Distribution by Gender and Race/Ethnicity: The Role of Occupations in an Intersectional Framework with 12 Groups *

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Abstract

If gender and race/ethnicity did not privilege some groups and harm others in the labor market, one would expect that groups that do not differ in terms of human capital, geographic location, and other basic characteristics would earn wages around average. However, our counterfactual analysis shows substantial disparities among our 12 gender–race/ethnicity groups. All female groups, except Asians, have conditional wages well below average, especially, Native American, Black, and Hispanic women. Moreover, all female groups have conditional wages below those of any male group (except Asian women, who rank above Black men). Male advantage seems to be concentrated in two races, Asians and Whites; the other male groups have conditional wages either below average (Black men) or around average (Hispanic, Native American, and “other race” men). Our intersectional framework allows delving deeper into the gender and race penalties. White women’s gender penalty is much larger than the racial penalty of any male (or female) group. Similarly, Asian women’s gender penalty is larger than the racial penalty of any male group except for Blacks. Distinguishing among more than 400 occupational categories, we find that underpayment within occupations harms especially Native American women whereas occupational sorting strongly impacts Black women (even after including controls). Black men’s occupational sorting also harms them after controlling for characteristics, a finding that we do not see in any other male group.

JEL Classification: D63; J15; J16; J71

Keywords: Earnings, Occupations, Gender, Race, Ethnicity, Intersectionality

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1. Introduction

In the literature on earnings differentials by gender and race/ethnicity, many scholars advocate for using an intersectional approach that accounts for both dimensions simultaneously so as to make visible that women's situation is not independent of their race and that racial disparities among women are not necessarily of the same magnitude as those among men (Kilbourne et al., 1994; Browne and Misra, 2003; Greenman and Xie, 2008; Mandel and Semyonov, 2016; Paul et al., 2018).

Much of this intersectional scholarship estimates the wage gap of Black women, who are usually compared to White women and Black men to determine, respectively, their racial and gender wage gaps (Kim, 2009; Dozier, 2010; Paul et al., 2018). The same type of analysis has also been applied to Hispanic and Asian women (Mar, 2000; Antecol and Bedard, 2002; Duncan et al., 2006) and, to a lower extent, Native American women (Kimmel, 1997; Burnette, 2017). However, there is little research analyzing the wage gaps of women and men of three or more racial/ethnic groups simultaneously, and those that do exist either undertake racial analyses separately for each gender or only compare women to men of the same race/ethnicity (Kimmel, 1997; McCall, 2001; Greenman and Xie, 2008).

This paper aims to fill this gap by exploring the wage advantage or disadvantage of White, Black, Hispanic, Asian, and Native American women and men, together with those of women and men of "other races," once differences in basic characteristics among these 12 groups are accounted for.¹ By doing this, we seek to answer the following types of questions. Do men of all racial/ethnic groups have wages above the average wage of the economy once we control for characteristics? Is the male advantage concentrated in particular racial groups? Does the privileged male groups' conditional earnings advantage arise from their occupational sorting or from receiving higher wages within occupations? Are there differences among the various racial male groups in this respect? What happens within occupations, would White men earn wages above the occupational average wage if all gender-race groups had the same basic attributes? Additionally, do all female groups have conditional wages below average? How do Native American women fare compared to similar

¹ In this paper, we use the terms Black and African American indistinctly.

Black or Hispanic women? Is the occupational sorting of Asian women as harmful as that of comparable White women? Is the problem of underpayment within occupations as important for Native American women as it is for other minority women and men? Is the gender penalty of women of any race/ethnicity larger than the racial penalty of men of any race/ethnicity?

To address these questions, this paper draws on the 2015–2019 5-year sample of the American Community Survey (ACS) and examines intergroup earnings differentials in an intersectional framework in which the above groups are jointly examined, which is this work’s distinctive feature. To control for the composition effect that may explain why the wages of some gender–race/ethnicity groups lag behind others’, we follow a methodology that allows expressing each group’s adjusted or conditional average wage as a proportion of the adjusted average wage of the economy. This allows us to extend comparisons beyond those of women and men of the same race (or the various races within a given gender), bringing a visually clear representation of the situation of our 12 gender–race/ethnicity groups simultaneously. Another distinct feature of our research is that it explores the role that occupational sorting plays in explaining the wage advantages and disadvantages of the groups by distinguishing among more than 400 categories.

To undertake the conditional analysis, first, we build a counterfactual economy in which workers’ attributes for each gender–race/ethnicity group are set equal to those of the reference group—White men—using a simple re-weighting scheme. To do this, we partition each gender–race/ethnicity group into subgroups or “cells” with specific attributes and replace the relative weight of each cell in the sample by that of the corresponding cell in the reference group while keeping the workers’ wages (and occupations) in that cell unaltered. Wage (and occupational) differences among gender–race/ethnicity groups that remain in this counterfactual economy can no longer arise from intergroup differences in the characteristics for which we accounted. This simple method, which as far as we know is proposed here for the first time, allows us to build what we label the “exact” counterfactual.

Second, we build another counterfactual economy using the semiparametric approach proposed in DiNardo et al. (1996), whose re-weighting scheme involves logit estimations, as Gradín (2013) adapted. Our empirical analysis shows that, in replicating the reference group’s distribution of characteristics, the “semiparametric” counterfactual is less accurate

than the “exact” counterfactual for two gender–race/ethnicity groups, Asian women and Hispanic men, although it coincides with the exact counterfactual for the remaining groups. This semiparametric approach’s advantage is that it provides a simple decomposition of the factors that explain the earnings differential between the actual and counterfactual distributions. We use Gradín’s decomposition, which as opposed to that of DiNardo and coauthors does not depend on the factors’ sequence, to determine the contribution of each covariate to the wage disadvantage (advantage) of each group and examine whether some attributes are more important for some groups than they are for others considering the 12 gender–race/ethnicity groups simultaneously.

Third, to determine the adjusted earnings of the 12 gender–race/ethnicity groups simultaneously, we combine these counterfactual methods with the intersectional approach proposed by Del Río and Alonso-Villar (2015), which allows exploring the effects of gender and race/ethnicity more broadly than has been done thus far. Our empirical strategy also allows shedding some light on how to compare the effect gender and race taken separately with its joint effect. Additionally, we use Del Río and Alonso-Villar’s decomposition to disentangle each group’s gain/loss associated with its occupational sorting (“between” component) from the earnings gap the group has within occupations (“within” component). We undertake this within-between decomposition using an occupational breakdown that accounts for 426 categories. This approach departs from what is usually done in the wage gap literature. On the one hand, our methodology allows exploring occupational segregation’s effect without including occupations as covariates, something that other scholars have long been claiming because occupational assignment is also the result of how gender and race groups have been treated in the labor market (Blau and Ferber, 1984; Black et al., 2008). On the other hand, we use a large list of occupational categories while analyses based on wage regressions usually include a low number because they require using a dummy variable per occupation.²

² Most wage gap studies use between 4 and 23 categories. One exception is Mandel and Semyonov (2016, p. 1045), who account for 80 titles. They acknowledge that “although aggregation into the two-digit classification may conceal part of the impact of occupations on earnings disparities, it was necessary for estimation of the models, because it was technically impossible to estimate the models with 400 detailed occupational categories.”

Fourth, we develop a decomposition of the between component to identify the occupations that contribute more to a group's earnings disadvantage, it being due to either its overrepresentation in low-paid occupations or its underrepresentation in the highly paid ones. This decomposition allows identifying the occupations that bring losses/gains to the groups beyond what is expected as based on the groups' characteristics, which is also a novelty in respect to what has been done in the literature. Additionally, we explore if the occupations in which a group's under- and overrepresentation causes an earnings disadvantage are also those in which that group's earnings lag behind other groups', and we quantify the incidence of this underpayment after controlling for characteristics.

This paper is structured as follows. Section 2 discusses previous literature, showing what is known so far and where some limitations are. Section 3 presents the data and methods. Section 4 offers the groups' earnings, expressed as a percentage of the average wage, after controlling for characteristics. The role each factor plays is also explored. The ranking of the groups is shown and the race/ethnicity and gender wage gaps are explored in an intersectional framework with 12 groups. Additionally, these conditional earnings are decomposed in the between and within components mentioned above. In Section 4, we provide a decomposition of the earnings gap that allows identifying which occupations bring more problems to deprived groups after controlling for attributes. Section 5 offers the main conclusions.

2. Background

2.1 Previous Findings

As Patten (2016) documented in a report of the Pew Research Center, racial/ethnic and gender wage gaps persist in contemporary U.S., despite the progress of some groups in past decades (Blau and Beller, 1992; Del Río and Alonso-Villar, 2015; Mandel and Semyonov, 2016; Wilson and Rogers, 2016). According to that study, in 2015, Black and Hispanic men's hourly wages were, respectively, 73% and 69% of that of White men. The only group that out-earned White men were Asian men, whose average wage represented 117% of that of the former. As for women, the hourly wages of Whites, Blacks, Hispanics, and Asians accounted, respectively, for 82%, 65%, 58%, and 87% of White men's wages. Therefore, women's

wages are lower than those of their male peers, with white women out-earning Black and Hispanic women but having lower earnings than Asian women.

To take into account that differences in characteristics may explain these groups' different positions in the wage distribution, Patten (2016) repeated the above analysis for individuals having bachelor's degrees or more education, showing that all of the above rankings remained the same. However, the literature does not show how the above gender–race/ethnicity groups rank after controlling for the various levels of education, together with other relevant characteristics, because these groups are not usually explored simultaneously.

There is evidence that Hispanic men's and women's wage gap, relative to their White counterparts, decreases substantially after accounting for education, English proficiency, and potential experience, which differs from what happens to Black workers (Trejo, 1997; Duncan et al., 2006).³ Although Black men's education attainments lag behind those of White men, Black men's earnings are also markedly lower than those of White men when standard human capital variables and additional controls are accounted for (Darity and Mason, 1998; Altonji and Blank, 1999; Paul et al., 2018).⁴ Black women's racial wage gap also persists after controlling for characteristics (Kim, 2002; Dozier, 2010), and despite it being lower than that of Black men, the wage gap of Black women vis-à-vis White men is larger than that of Black men (Kim, 2009; Paul et al., 2018). As for White women, the literature indicates they have lower earnings than comparable White men, with their gender gap being even larger than the racial gap of Black men (Paul et al., 2018).

With respect to Native Americans, a group that has received less attention in the wage gap literature than other racial/ethnic minorities, scholarship also shows they lag behind either their White or non-Native counterparts, not only before but also after accounting for differences in attributes, both in the case of women and men (Hurst, 1997; Burnette, 2017).

As for Asian women and men, most studies based on recent data claim these groups are not penalized in terms of earnings relative to their White peers, at least not those born in the U.S.

³ Mora and Dávila (2018) also show that Hispanic men's ethnic wage gap decreases substantially when controlling for education, experience, immigration status, and region. However, much of the gap between Hispanic women and White men remain after controlling for the same characteristics due to the gender effect.

⁴ Some argue that the racial penalty would disappear if instead AFQT (Armed Forces Qualifying Test) scores were used, a matter not free of controversy.

(Sakamoto and Furuichi, 2002; Takei et al., 2012). For foreign-born Asians, the results are mixed and depend on whether workers were schooled in the U.S. or abroad (Zhen and Xie, 2004; Kim and Sakamoto, 2010; Kim and Zhao, 2014). Those who obtained their bachelor's degrees in the U.S. seem to have achieved parity with Whites whereas those who completed their college education abroad still lag behind.

The covariates usually employed in the wage gap literature have various explanatory power depending on the group under consideration. Education plays an important role in explaining the racial/ethnic wage gaps of Black and Hispanic men (or Asian men's earnings advantage), but it does not explain the gender wage gaps of White, Black, and Hispanic women. Experience is usually computed based on years of schooling and age because most data sets do not provide actual experience. However, actual and potential experience do not necessarily play the same role in the analysis. When using youth surveys that include this information, some studies show that, whereas potential experience does not help to understand the racial wage gaps of Black women and men, actual experience does (Antecol and Bedard, 2002, 2004). Location is another relevant variable in explaining intergroup wage disparities. The presence of racial minorities, especially Asians, in large cities tends to be larger than that of Whites. Given that urban areas and large cities tend to pay more than other areas, many studies include controls for residence in metropolitan areas (or the cost of living), which explains part of the wage differential between Whites and racial/ethnic minorities, for both women and men (McHenry and McInerney, 2015; Burnette, 2017; Paul et al., 2018). Controlling for region is also common practice in racial analyses (Blau and Beller, 1992; Antecol and Bedard, 2002, 2004; Bailey and Collins, 2006; Burnette, 2017). Marital status, number and/or age of children, and part-time status are also control variables usually employed in the wage gap literature, especially in gender analyses or when comparing female groups by race (Blau and Beller, 2002; Antecol and Bedard, 2002, 2004; Bailey and Collins, 2006; Dozier, 2010; Mandel and Semyonov, 2016).

2.2 Exploring Gender–Race/Ethnicity Groups: Some Limitations

Thus far, the wage gap literature has focused on selected gender–race/ethnic groups, depending on the particular question researchers aim to explore. These studies usually distinguish two races/ethnicities, sometimes three, and either conduct separate analyses for

men and women or exclusively focus on one gender (Kimmel, 1997; Antecol and Bedard, 2002; 2004; Alon and Haberfeld, 2007; Kim, 2009; Mandel and Semyonov, 2016).⁵ The fact that these studies encompass different target populations,⁶ employ different data sets, explore either annual or hourly wages, and include different control variables in their analyses make it difficult to have a broad picture of the various gender–race/ethnicity groups’ simultaneous positions. We may know how White women fare compared to either their White-male or Black-female peers, but we do not know much about whether White women out-earn comparable Hispanic or Native American men. In the same way, we may know how Black women are relative to Black men or White women, but we know little about how they fare compared to Hispanic or Native American women.

To our knowledge, the wages of White, Black, Hispanic, Asian, Native American, and “other race” women and men have not been explored simultaneously after controlling for characteristics. Therefore, little is known about how ranking these 12 groups would be if they did not differ in terms of composition (i.e., if they were similar in terms of education credentials, immigration profile, region of residence, and other relevant attributes) or whether some factors are more important to explain some groups’ situation than they are for others. We also know little about whether, after controlling for characteristics, the role that occupations play in explaining women’s earnings differ by race/ethnicity and whether the concentration of Asian and White women in low-paid occupations is more intense than that of any disadvantaged minority men.

We do know the role that occupations play before controlling for characteristics. Thus, using a detailed occupational classification, Del Río and Alonso-Villar (2015) show that occupational segregation explains most of the earnings disadvantage of African American and Hispanic women and men, and at least half of the earnings advantage of White and Asian men. They also document that Asian women constitute the only female group with an occupational sorting that benefits them (although it only allows them to have wages slightly

⁵ An exception is Greenman and Xie (2008), who explore 19 racial/ethnic groups (a set that includes several ethnic groups within Asian and Hispanic populations and bi-racial groups) to study the variation of the gender wage gap by race/ethnicity among U.S.-born workers. Their approach differs from ours given that they estimate a wage equation using gender and race as the only regressors. Additional controls are only used to explore interaction effects between gender and race for women.

⁶ Not only because of the specific gender–race/ethnicity groups they deal with but also their target subpopulations within those groups (such as the young, college educated, or native born).

above the average wage) and White women get most of their earnings disadvantage from being paid below average within occupations (although their occupational sorting does not benefit them, either). However, that study does not show whether differences in the groups' occupational sorting is mainly the result of intergroup differences such as education, age, immigration profile, etc. or if these occupational disparities would persist had the groups been similar in those attributes.

The literature documents that including a short list of occupations as control variables in wage regressions helps to reduce intergroup wage disparities. Thus, using the Blinder–Oaxaca decomposition and 20 occupational categories, Blau and Kahn (2017) claim that occupations play an important role in explaining the gender wage gap. Employing the same decomposition and a similar number of occupations, Paul et al. (2018) also show that occupations explain an important share of the wage gap between Black and White men, this factor being more important than education. They also find that occupations explain a large part of Black women's racial and gender gaps. However, including occupations as control variables does not seem the best way to explore intergroup wage disparities given that, as already mentioned, occupational sorting is not a gender- and race-blind mechanism (Blau and Ferber, 1984; Black et al., 2008).

By distinguishing among more than 400 occupational categories, but without including them as control variables, we build a counterfactual economy that allows delving deeper into the role that occupations play in explaining the wage differences among White, Black, Hispanic, Asian, Native American, and “other race” men and women were these groups analogous in terms of education credentials, immigration profile, English proficiency, region of residence, metropolitan area size, and other relevant attributes. Moreover, we do so in an intersectional framework in which each of the 12 gender–race/ethnicity groups can be compared to any other, even if they differ in terms of both gender and race/ethnicity, thus expanding intergroup comparisons.

3. Data and Methodology

We use the 2015–2019 5-year sample of the American Community Survey (ACS) provided by the Integrated Public Use Microdata Series (IPUMS; Ruggles et al., 2020). The

harmonized information the IPUMS provided distinguishes among 426 occupational categories (with employment during this period), which allows us to offer a relatively good estimate of the role that occupations play in explaining intergroup wage disparities. We proxy the wage of each occupation by the average hourly wage, estimated after trimming the tails of the hourly wage distribution (wages below the 1st percentile or above the 99th percentile of positive values in that occupation). The corresponding workers are eliminated from the analysis, which reduces the sample to 6,668,782 workers.

We partition the population into 12 gender–race/ethnicity groups, which result from considering women and men of 6 racial/ethnic groups: Hispanics (irrespective of race), non-Hispanic Whites, Blacks, Asian (Chinese, Japanese, and other Asians or Pacific Islanders), and Native Americans (American Indians and Alaskan natives), and “other races” (non-Hispanics that self-report some other race or more than one race).

3.1 The Role of Occupations in the Wage Gap

For each of these groups, denoted by g , we define the group’s earnings gap as the differential between its average wage and the economy’s average wage divided by the latter:

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

where $\frac{c_j^g}{C^g}$ is the share of group g in occupation j , $\frac{t_j}{T}$ is the employment share accounted for by occupation j , w_j represents the average wage of occupation j , w_j^g is the average wage that group g receives in occupation j , and $\bar{w} = \sum_j \frac{t_j}{T} w_j$ is the economy’s average wage. Following

Del Río and Alonso-Villar (2015), $EGap^g$ can be decomposed into two terms, one showing the group’s (per capita) monetary advantage or disadvantage arising from its uneven distribution across occupations (Γ^g) and another indicating the (per capita) monetary loss or

gain the group has within occupations given that it can be paid below or above other groups (Δ^g):⁷

$$EGap^g = \underbrace{\sum_j \left(\frac{c_j^g}{C^g} - \frac{t_j}{T} \right) \frac{w_j}{\bar{w}}}_{\Gamma^g} + \underbrace{\left[\sum_j c_j^g (w_j^g - w_j) \right]}_{\Delta^g} \frac{1}{C^g \bar{w}}. \quad (2)$$

If group g 's earnings are below average, $EGap^g$ will take a negative value, due to how the group tends to concentrate in low-paid occupations ($\Gamma^g < 0$), how the group has lower wages than other groups working in the same occupations ($\Delta^g < 0$), or a combination of both factors. Using this decomposition, we can determine easily whether occupational sorting is important in explaining group g 's earnings gap.

Given that the $EGap^g$ of each group and its two components are expressed as a proportion of the economy's average wage, we can compare the role that segregation plays for our 12 groups simultaneously. Moreover, we can do this not only before but also after controlling for characteristics, which makes this approach especially convenient for disentangling the effects of gender and race/ethnicity in an intersectional framework. To simplify notation, in the empirical sections we drop the superscript g that refers to each group.

3.2 Counterfactual Analysis

To control for characteristics, we build two counterfactual economies, one called the “exact” counterfactual and the other the “semiparametric” one, in which all groups have the same attributes as White men have (see Appendix for technical details). Consistent with the discussion presented in Section 2, our list of covariates are: education attainment (5 levels: less than high school, high school diploma, some college, bachelor's degree, and master's or doctoral degree); age (3 categories: younger than 36, between 36 and 55, and 56 or older);

⁷ Note that $\Gamma^g = \frac{1}{C^g} \sum_j C^g \left(\frac{c_j^g}{C^g} - \frac{t_j}{T} \right) \frac{w_j}{\bar{w}} = \frac{1}{C^g} \sum_j \left(c_j^g - C^g \frac{t_j}{T} \right) \frac{w_j}{\bar{w}}$. Therefore, this represents the per capita loss or gain group g has due to its underrepresentation in some occupations ($c_j^g < C^g \frac{t_j}{T}$) and overrepresentation in others ($c_j^g > C^g \frac{t_j}{T}$), expressed as a proportion of the economy's average wage.

years of residence in the U.S. (3 categories: U.S. born, living up to 15 years in the U.S., and more than 15 years), metropolitan area size (2 categories: living in an area with 1 million people or more and living elsewhere); English proficiency (2 categories: speaking only English at home or speaking English well/very well and speaking not well or not at all); region of residence (4 census regions: Northeast, Midwest, South, and West); part-time work (2 categories: working up to 34 hours per week and working more); children (2 categories: having at least one child of up to 15 years of age and not having a child of that age); and living with a significant other (2 categories: living with a partner, either married or cohabiting, and not living with a partner).⁸

To build the “exact” counterfactual, we split each group into subgroups or “cells” that result from specific combinations of our covariates (e.g., U.S. born, 30 to 54 years of age, speaking only English, living in a metropolitan area with a population above 1 million located in the Northeast region, working full time and living with a partner with no children). We observe how the individuals of that group in each cell are distributed across our 426 occupations and keep that distribution unchanged (we also keep these individuals’ wages unaltered). However, we change the weight that each cell has in the group to make it equal to that of White men with the same characteristics. This process is formalized in the Appendix.

Following DiNardo et al. (1996) and Gradín (2013), we also build a “semiparametric” counterfactual in which the reweighting scheme involves calculating the probability of being of the reference group given those characteristics, in relation to the probability of being in the own group, using a logit model in which we only have individuals from these two groups (see Appendix). This method’s advantage is that it allows for an easy decomposition of the difference between conditional and unconditional values. To determine the contribution of each covariate (or set of covariates) to this difference, we follow Gradín (2013), who provides an exact decomposition based on the Shapley value, which does not depend on the sequence

⁸ Taking into account the number of observations of some of the gender–race groups in the sample (see Table A1 in the Appendix), we opt for not increasing the number of categories considered in the analysis. To explore whether having a bachelor’s degree in a STEM (Science, Technology, Engineering, and Mathematics) field could affect the results for the Asian population, we have also considered an alternative categorization of education that allows accounting for STEM studies without increasing the number of education categories (less than high school, high school, some college, tertiary education in a non-STEM field, and tertiary education in a STEM field) and the results did not change. We have also explored using children below 6 years of age, rather than 16, to check if our results were robust against this threshold and we found they were.

of factors, thus improving DiNardo and coauthors method. In our empirical analysis, we follow this technique to determine the role each factor plays in explaining intergroup wage differences between conditional and unconditional values.

4. Wages and Occupations in an Intersectional Framework with 12 Gender–Race/Ethnicity Groups

Figure 1 displays the earnings advantage or disadvantage (*EGap*) of each of the 12 gender–race/ethnicity groups, decomposed into the Γ and Δ components, using the actual data. As already mentioned, for ease of notation, we drop the superscript g referring to the group. A group with a positive *EGap* has an average wage above the economy’s average wage (expressed in percentage terms) whereas a negative *EGap* means a wage below average. The wage discrepancy between any two groups can be obtained easily by subtracting their corresponding *EGap* values. A positive (respectively, negative) Γ value means the group tends to concentrate in highly paid (respectively, low-paid) occupations. Analogously, the value of Δ is positive (respectively, negative) if within occupations the group tends to have wages above (respectively, below) the average occupational wage.

The chart shows that Asian and White men have wages far above the economy’s average wage (41% and 22%, respectively). However, the wages of Hispanic, Black, and Native American men are below average (20%, 17%, and 16%, respectively), and those of “other race” men are close to the average wage. All female groups have wages below average (except Asian women whose earning gap is 12% above average). This is particularly the case of Hispanic, Native American, and Black women, whose (negative) earnings gaps are 31%, 29%, and 24%, respectively.⁹ The analysis also reveals that, except for White women, occupational sorting represents an important share of the groups’ *Egap*. Moreover, most of the earnings disadvantage of Black, Hispanic, and Native American women and men arise

⁹ Intergroup wage disparities are larger now than a decade ago (Del Río and Alonso-Villar, 2015), in part due to Asians’ wages rising.

from their concentration in low-paid occupations ($\Gamma < 0$), although wage disadvantages within occupations are also important ($\Delta < 0$), especially for female groups.¹⁰

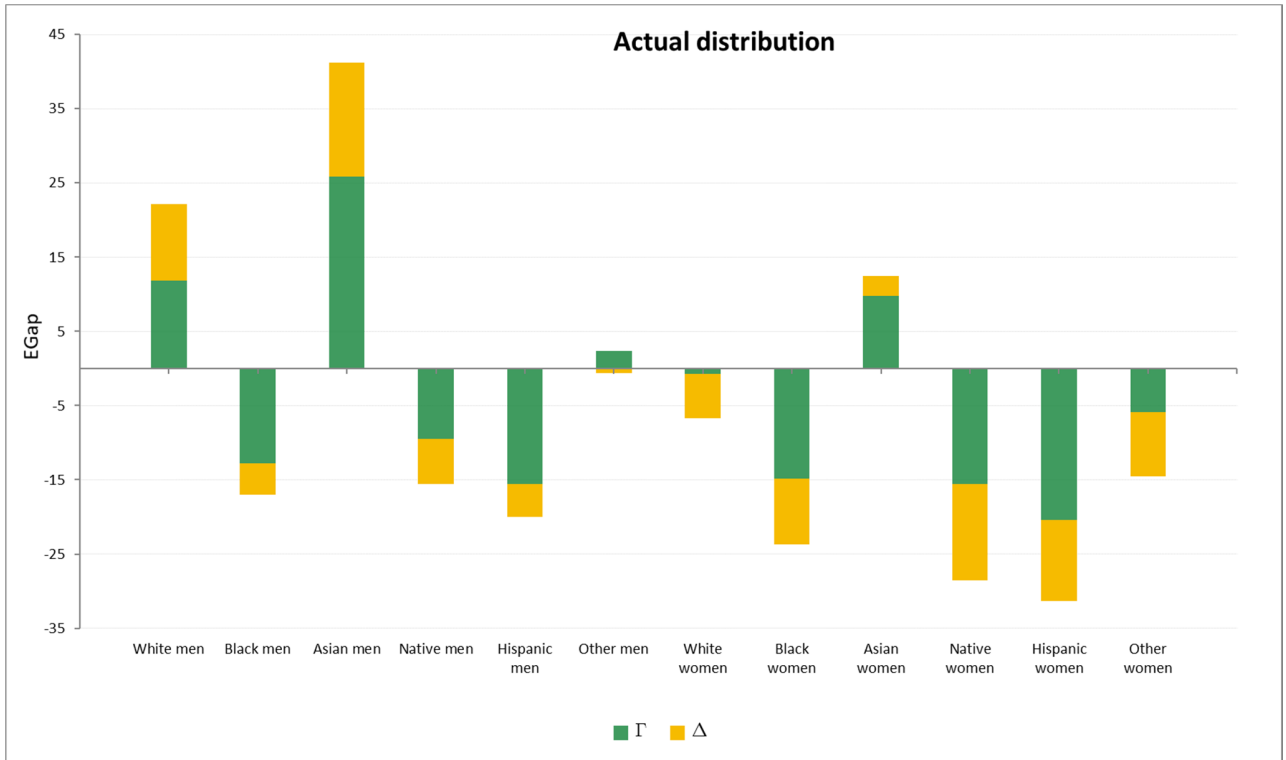


Figure 1. The earning gap (*EGap*) of each group (with respect to average wage) and its two components, occupational sorting (Γ) and within-occupation wage gap (Δ), in the actual wage distribution.

Figure 1 shows the situation of the groups in the actual wage distribution, but we may wonder if this picture is the result of gender–race/ethnicity groups facing different levels of integration into the labor market or instead stems from how these groups have different characteristics (making them apply to different job types). Thus, for example, if the groups differ in terms of education attainment, their occupational sorting disparities may just be a reflection of differences in education.

4.1 The Exact Counterfactual

To account for differences in characteristics, first, we build the exact counterfactual economy, as explained in the methodological section. For each gender–race/ethnicity group,

¹⁰ This is especially the case for White women, for whom almost 90% of their *EGap* comes from this factor.

we replace the relative weight of each cell (which is defined by the combination of 9 characteristics) by the weight that cell has in the reference group, which is that of White men. However, we keep unaltered the wages and occupational sorting of the individuals in that cell. Consequently, although in our counterfactual economy, all the gender–race/ethnicity groups have the same characteristics, we may still find that occupations play a role in explaining intergroup wage disparities so long as the occupational distribution of individuals with certain attributes vary by gender and/or race/ethnicity.

Figure 2 shows this counterfactual analysis. We see that wage disparities among groups decrease after controlling for characteristics. Notwithstanding, if all groups had the same educational attainments, English proficiency, immigration rates, location, etc., we would still see large wage disparities, both arising from the groups' different occupational sorting (Γ) and from intergroup disparities within occupations (Δ). Thus, Asian men have an earnings advantage of 20% of the average wage of the counterfactual economy and the advantage of White men is 17%, despite their having the same characteristics as the other groups. A large share of this advantage stems from these groups' concentration into highly paid occupations, although they also earn higher wages within occupations. Note that Asian men's wages are slightly above (3%) those of comparable White men, which departs from previous findings for earlier periods (Zhen and Xie, 2004).¹¹

¹¹ However, if we excluded “couple,” “children,” and “part time” covariates, Asian men's wages would be lower than that of their White peers, which suggests the ranking between Asian and White men may depend on controls that are not usually employed in racial analyses among men. The small advantage we find in our analysis (using 9 covariates) may arise from factors for which we do not control, as is the higher probability of Asian men to pursue high-earning majors (Xie and Goyette, 2003). In explaining Asian men's wages, the literature suggests that college prestige and field of study are important factors (Kim and Sakamoto, 2010). We do not have information on college prestige in our data set and although field of study is included, our exploration using the 9 controls when the joint category master and bachelor's degree is additionally split into STEM and non-STEM studies also suggests that Asian men out-earn White men.

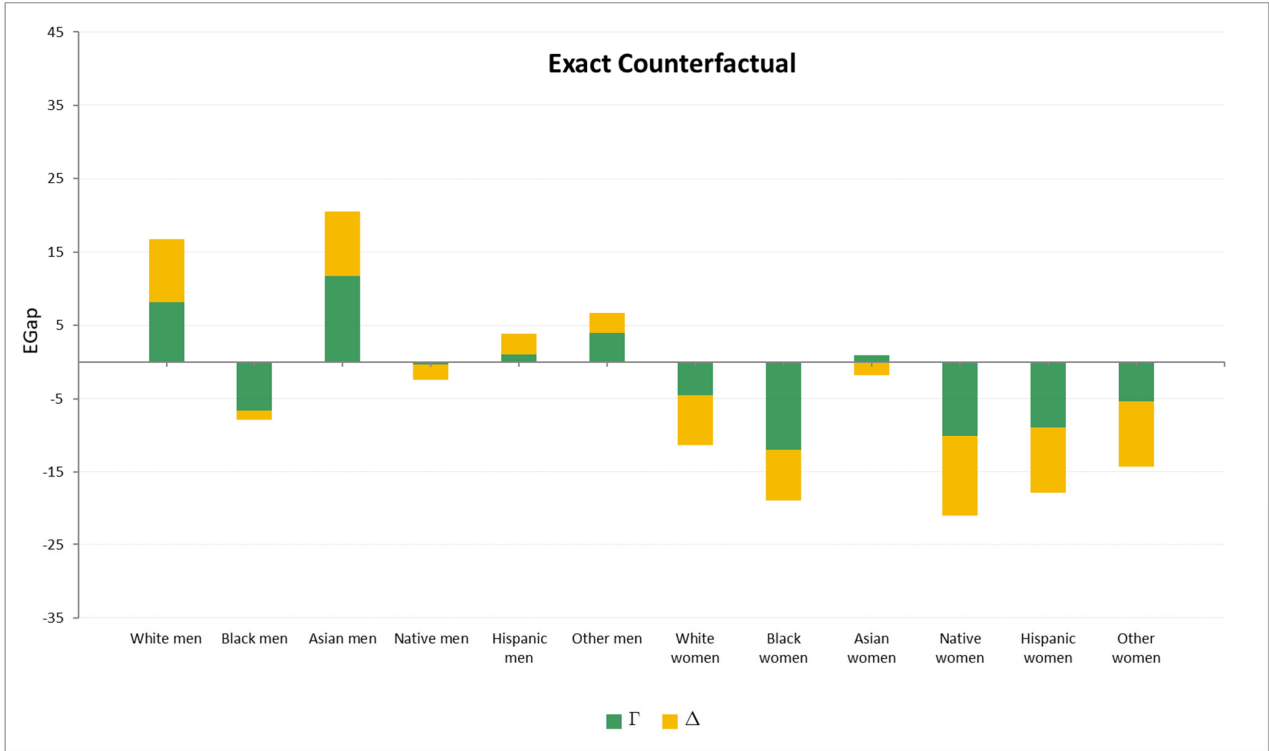


Figure 2. Each group’s earning gap (*EGap*; with respect to average wage) and its two components, occupational sorting (Γ) and within-occupation wage gap (Δ), in the exact counterfactual wage distribution.



The situation of other minority men is different. Consistent with prior research, Native American and Hispanic men lag behind White men after controlling for characteristics (Hurst, 1997; Mora and Dávila, 2018). Native American and Hispanic men have conditional wages around average, which implies they do not have the male premium that White and Asian men possess, although they are not deprived groups in the economy as a whole. The situation is worst for Black men because their conditional wages are below average (although closer to the average than the unconditional ones). Black men earn less than any other male group with the same characteristics. This is consistent with the racial Black–White penalty shown in previous studies (Trejo, 1997; Darity and Mason, 1998; Paul et al., 2018), although our analysis takes a step further documenting and quantifying Black men’s wage disadvantage with respect to Asian, Hispanic, Native American, and “other race” men (28%, 12%, 5%, and 15%, respectively). Moreover, we find that Black men’s occupational sorting harms them even after controlling for characteristics, a finding that we do not see in any other male group.

Figure 2 also shows that the wage advantage that Asian women have in the actual distribution would vanish if we controlled for characteristics. If this group's composition was similar to that of White men, its earnings would equalize the economy's average wage. However, the situation is worse for the other female groups. The conditional wages of Native American, Black, Hispanic, "other race," and White women are well below average (21%, 19%, 18%, 14%, and 11%, respectively), a large part of these disadvantages stem from their high concentration in low-paid occupations, especially Black women, although all these female groups are also strongly disadvantaged within occupations. The fact that Hispanic, Black, and Native American women have lower wages than comparable White women whereas Asian women out-earn their White peers is in line with prior research (Kim, 2002; Dozier, 2010; Burnette, 2017; Mora and Dávila, 2018)¹² and is the fact that female groups' earnings are lower than those of their same-race male peers (Paul et al., 2018; Mora and Dávila, 2018). However, our intersectional analysis allows pushing the analysis further. We show that the female disadvantage becomes more evident after controlling for characteristics: White, Black, Hispanic, Native American, and "other race" women have conditional wages below those of any male group and Asian women's earnings are below those of any male group except for Blacks (and Native Americans, whose *EGap* is similar to that of Asian women).¹³ Moreover, our approach allows determining the gender, race, and gender–race wage gap of a group easily given that all groups' wages are expressed as a proportion of the average wage in the counterfactual economy. A group's earnings below (respectively, above) that of another group implies a penalty (respectively, premium) with respect to that group in terms of gender, race/ethnicity, or a combination of both. Moreover, a group's total penalty (or premium) with respect to White men (the group that many studies recommend to use as reference to analyze the situation of any other gender–race groups) can be expressed as the

¹² The advantage of Asian women vis-à-vis White women may arise from the fact that Asians have a larger probability of pursuing high-earning majors (Xie and Goyette, 2003). Kim and Zhao (2014) claim that when accounting for college prestige and field of study, college-educated Asian women either have wages similar to those of their White peers or below (depending on whether they are U.S. schooled or not). However, in our exploration based on STEM versus non-STEM studies mentioned before, we find that Asian women out-earn White women.

¹³ The ranking of female groups is almost the same in the actual and counterfactual economy (except that Hispanics are slightly above Blacks and Native Americans are in the counterfactual). Ranking male groups in the conditional analysis is also the same as in the unconditional one except that the positions of Hispanics and Native Americans switch and depart from that of Black men.

sum of a gender and a racial penalty (or premium) using a consistent sequence of comparisons. Figure 3 provides the gender, racial, and gender–race earnings gaps of the groups (obtained from Figure 2).

For example, we see that Black women earn 7.4 percentage points (p.p. hereafter) of the average wage less than White women (i.e., the women’s Black–White racial wage penalty is 7.4 p.p.). Black women’s gender wage penalty, which results from comparing them to Black men, is 11 p.p. To compare Black women to White men, we can follow two different paths, depending on whether Black men or instead White women are the intermediate group used in the comparisons (i.e.,  or ). However, note that regardless of the path taken, the wage differential between Black women and White men is the same ($-7.4 + -28.1 = -11 + -24.5 = -35.5$). If we follow the first path, the gender gap refers to the Black population and the racial gap to men, whereas if we take the second path, the racial gap refers to women and the gender gap to the White population. Both paths involve a compatible and complete sequence of comparisons.¹⁴

Notice that our approach differs from Kim (2009) and Paul et al. (2018) given that they compare the sum of the racial and gender penalties of Black women (obtained from comparing these women to White women and Black men, respectively) to the total penalty of Black women (relative to White men). They do so because their methodological approach, based on standard wage equations, requires keeping a common group—Black women—in these three pairwise comparisons. Consequently, by comparing Black women to White men in the way they do, the authors are not actually following a complete and compatible sequence of comparisons, something that our methodology allows us to do. This explains why in their analyses, the total penalty of Black women differs from the sum of their gender and race penalties. Given that, as Figure 3 illustrates, White women’s gender penalty is larger than that of Black women and Black men’s racial penalty is larger than that of Black women, the total penalty of Black women is larger than the sum of their gender and racial penalties, which is what the literature calls “interaction effect”. We certainly find that Black women have a double disadvantage (which we also find for Native American and Hispanic women, and to a lower extent “other race” women) but as opposed to previous research, we consider

¹⁴ Our reasoning follows Del Río and Alonso-Villar (2019), who explore the sexual orientation wage gap of racial minority women and men.

misleading to identify/quantify an interaction effect by comparing a group's total penalty with the sum of its racial and gender penalties. To illustrate this, consider a hypothetical scenario where the average wage of White women and Black men was similar to that of White men. In this case, the total penalty of Black women would be lower than the sum of their race and gender penalties. Following the above rationale, Black women would have a positive interaction effect, which would be hard to justify.

Figure 3 also illustrates that the racial penalties of Blacks, Hispanics, Native Americans, and "others" are larger for men than they are for women of the same race/ethnicity. On the contrary, for Asians, the racial wage advantage is more pronounced among women. We also see that White women have the largest gender penalty. Moreover, White women's gender penalty is larger than Black men's racial penalty, which is the group with the largest racial penalty.¹⁵

¹⁵ These results are in line with those obtained by Greeman and Xie (2004), who explore 19 racial groups using a more restricted sample of workers (25–55 years old and U.S. born), and Paul et al. (2018), who study Black and White workers.



Figure 3. *EGap* differentials among gender-race/ethnicity groups in the exact counterfactual wage distribution.

4.2 The Semiparametric Counterfactual: Factor Decomposition

To explore the role each factor plays in explaining the difference between groups' situation before and after controlling for characteristics, we build a new counterfactual, which we label the semiparametric counterfactual (see Figure 4). Here, the re-weighting scheme involves logit regressions (DiNardo et al., 1996; Gradín, 2013). The advantage of this counterfactual is that it allows for an easy decomposition of the factors involved. The disadvantage is that for some groups, the weight of some cells in the counterfactual economy may depart from that of the reference group, because the fit is not as precise as that of the exact counterfactual. This is the case of Asian women and, to a lower extent, Hispanic men, for whom the estimated weight for the highest education level (i.e., master's degree or above) using the logit regression is higher than that of White men (which is the weight we should approximate). This is why Asian women and Hispanic men have higher wages in the semiparametric counterfactual (Figure 4) than in the exact counterfactual (Figure 2). For the other gender–race/ethnicity groups, the estimated wages barely change between the two counterfactuals.

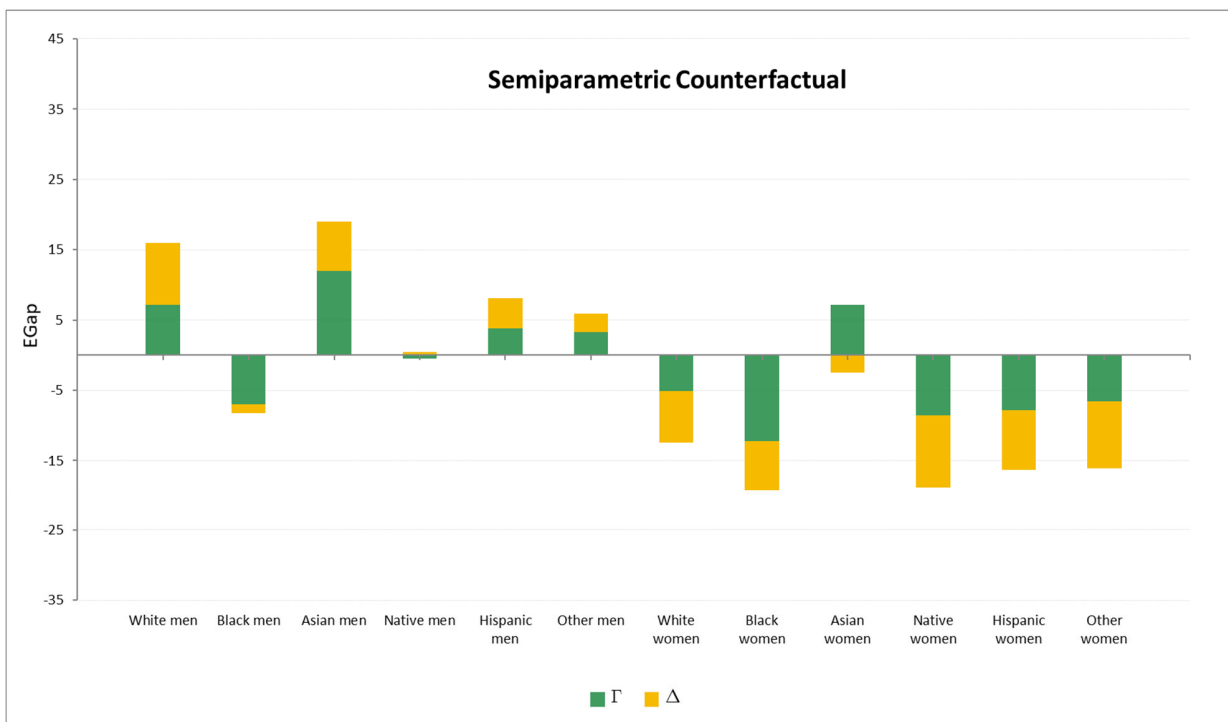


Figure 4. Each group's earning gap ($EGap$; with respect to average wage) and its two components, occupational sorting (Γ) and within-occupation wage gap (Δ), in the semiparametric counterfactual wage distribution.

Figure 5 provides information about the role each covariate plays in explaining the difference between the *EGap* in the actual distribution and that in the semiparametric counterfactual. Factors with positive values benefit the group in the actual distribution, making the group have larger earnings there than in the counterfactual. Conversely, factors with negative values penalize the group in the actual distribution, making the group's earnings lower than in the counterfactual distribution.

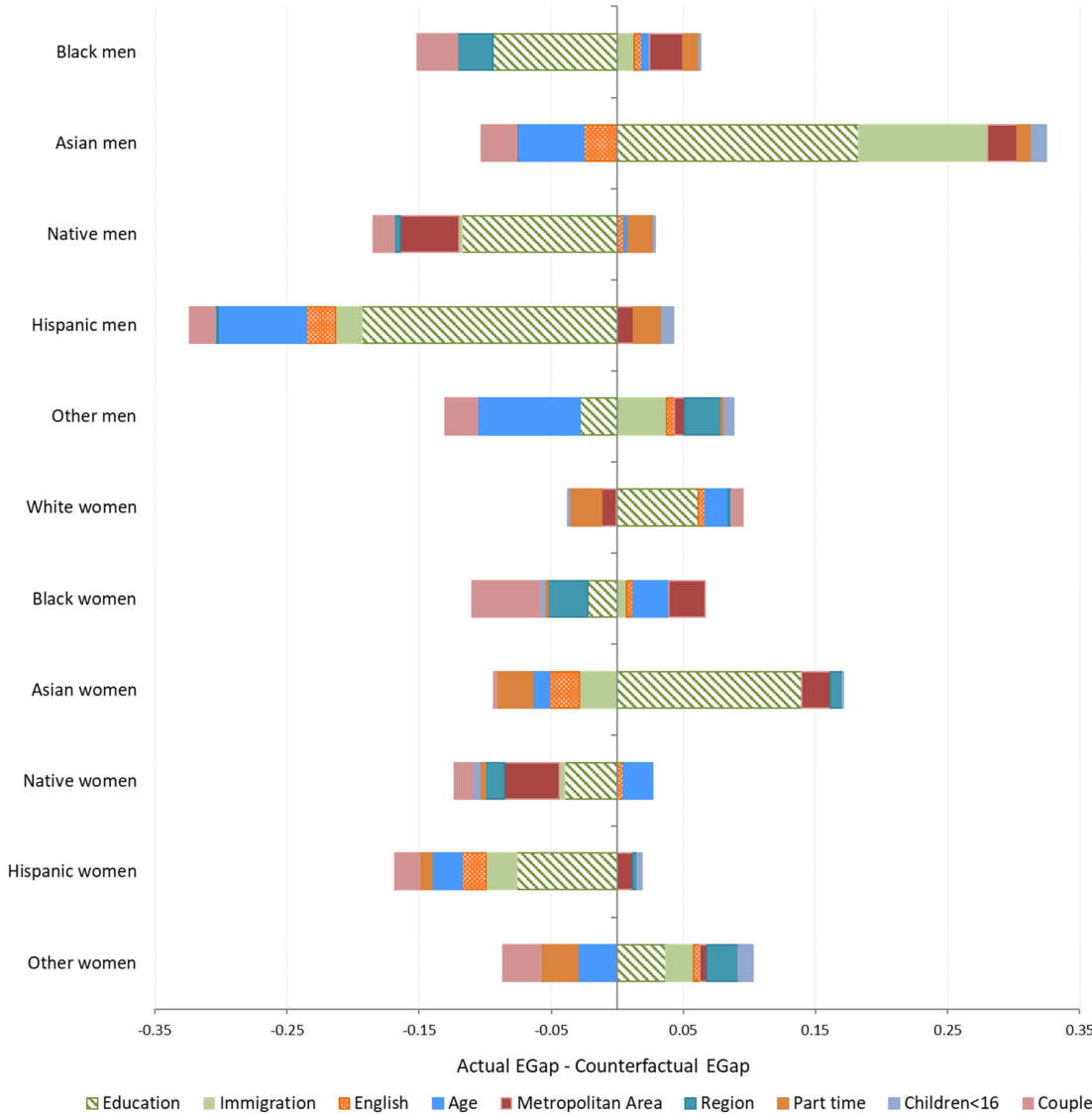


Figure 5. Actual *EGap* minus semiparametric counterfactual *EGap* and factors' contributions.

Let us start examining Black men. For this group, the right bar is smaller than the left bar, which implies this group has higher wages in the counterfactual economy. It can also be seen that in explaining the change between the two scenarios, “education” is the most important factor. If Black men had the same educational attainments as White men, their earnings would be larger than they actually are (this is why education has a negative value). “Region” and “couple” contribute negatively too, although they are of much lower magnitude. Part of Black men’s disadvantage in the actual distribution comes from their higher concentration in the South, which has lower wages than other regions.¹⁶ It can also be seen that family structure does not benefit them. If the proportion of Black men living in couples (either married or cohabiting) were as high as that of White men, their wages would be higher, which suggests that unpartnered Black men fare worse than the partnered ones. On the contrary, living in large metropolitan areas contributes positively, which implies that residential location is more beneficial for Black men in the actual distribution than in the counterfactual. If Black men had a larger presence in small metropolitan areas or in rural areas, their wages would be lower than they actually are. The contribution of the other variables is almost insignificant.

“Education” is also the most important factor for Asian men, although in this case the value is positive. This means that the main reason for explaining why Asian men’s wages are larger in the actual distribution is education (their educational achievements are larger than those of White men, therefore when we artificially reduce them, their wage falls). The second most important factor for this group is “immigration.” Surprisingly, their immigration profile seems to benefit them. Asian men’s wages would decrease if their immigration rate were set equal to that of White men. This suggests that, keeping other characteristics constant, immigrant Asian men tend to have higher wages than the U.S. born, which evidences a distinctive pattern for this group, a pattern that Asian women do not share.¹⁷ We also see that “immigration” and “English proficiency” capture different aspects of the Asian male population because they play opposite roles (“English proficiency” has a negative value).

¹⁶ The (hourly) average wage in the South is \$23.27 whereas in Midwest, West, and Northeast it is \$23.41, \$26.18, and \$27.74, respectively.

¹⁷ This is in line with Zhen and Xie (2004), who find that college-educated Asian men born abroad and educated in the U.S. earn more than similar U.S.-born Asian men.

Finally, note that part of Asian men's wage disadvantage in the actual distribution comes from their age structure, if they were older, the group's wage would rise.¹⁸

"Education" and, to a lower extent, "age" are the most important factors that explain the difference between unconditional and conditional wages for Hispanic men. If they had the same educational achievements and age structure as White men, Hispanic men's wages would increase substantially. "Education" is also the main factor for Native American men, followed at a certain distance by "region." However, for "other race" men, who is an especially young group, "age" is basically the most important factor that explains their disadvantage in the actual distribution.

"Education" is also the main explanatory factor in the case of White and Asian women (together with "other" women). Similar to Asian men, these groups' wages, especially those of Asian women, would decrease if these women had the same educational achievements as White men (which are lower than theirs are). For these women, working "part-time" also plays a role, although small. If they had lower rates of part-time workers, their wages would increase slightly. In addition, Asian women's wages would increase if they had lower immigration rates and higher English proficiency than they actually have.

"Education" further helps to explain, to a large extent, why Hispanic women's earnings are larger in the counterfactual distribution than in the actual (although their deficit in education is lower than that of Hispanic men). "Age," "immigration," and "English proficiency" are factors that go in the same direction as "education," although of a much lower magnitude.

On the contrary, "education" is not what can explain why Black and Native American women have wages so low in the actual wage distribution. In fact, for Native American women, the role that education plays in explaining the difference between the actual and counterfactual distributions is not more important than "metropolitan area." Moreover, for Black women,

¹⁸ Although the distribution of "couple" is similar for White and Asian men, the effect of this factor is negative for Asian men. This is because the distribution of partnered Asian men across education categories differs from that of White men (the latter having a lower presence in the upper educational levels). In other words, although the effect of "couple" alone is negligible, this control variable plays a role when combined with other control variables (e.g., education). Thus, we find the effect of reducing Asian's men education (to make this group have the same education structure as White men's) involves rising the weight of partnered individuals within those with tertiary education. Given that partnered individuals out-earn unpartnered ones, this change raises Asian men's wages. This explains why Asian men improve their position in the ranking when accounting for "couple," in addition to standard control variables.

“couple” is the most important factor. If the proportion of Black women living in couples increased, while keeping unchanged other characteristics, their wages would rise. This suggests that the wages of Black women living without a partner are lower than those with a partner, which is in line with what we observed in the case of Black men, except that the effect’s magnitude is now larger. Regional location also penalizes them, although to a lower extent than “couple.” On the contrary, their age structure and concentration in large metropolitan areas benefit them, although only slightly.¹⁹ Given the effects of the different covariates, we conclude that if we removed the effect of “couple,” Black women’s wages would be similar in the actual and counterfactual distributions because the effect of “age” and “metropolitan area” would cancel those of “region” and “education.”

5. Looking at Occupations: Representation and Wages

Thus far, we have explored whether the wage disadvantage of a group g arises from its overrepresentation in low-paid occupations (and underrepresentation in the highly paid) or from earning lower wages than other groups working in the same occupations. Now, we delve into this by identifying the occupations that contribute more to these two components. Taking into account that the summation of a group’s shares over all occupations, and also the summation of the employment shares of all occupations, is equal to 1,²⁰ we can rewrite Γ^g as follows:

$$\Gamma^g = \sum_j \left(\frac{c_j^g}{C^g} - \frac{t_j}{T} \right) \frac{w_j}{\bar{w}} = \sum_j \underbrace{\left(\frac{c_j^g}{C^g} - \frac{t_j}{T} \right)}_{\Gamma_j^g} \frac{(w_j - \bar{w})}{\bar{w}}. \quad (3)$$

¹⁹ The effect of “age” is unexpected (Black women is a younger group than White men’s). This may be because the role that “age” plays in isolation is not the same as it does in combination with other covariates. We find that to adjust for “age” after controlling for “couple” in the subgroup of Black women living with a partner, we have to increase substantially the weight of the young, who have lower wages than older ones. In other words, when combined with other covariates, the age structure of Black women in the actual distribution is more beneficial than the one they reach in the counterfactual distribution.

²⁰ In other words, $\sum_j \frac{c_j^g}{C^g} = \sum_j \frac{t_j}{T} = 1$.

Note that Γ_j^g is positive if group g is either overrepresented in an occupation j with an average wage above the economy's average wage or underrepresented in an occupation j with an average wage below average. If the group is instead underrepresented in a highly paid occupation or overrepresented in a low-paid one, Γ_j^g will be negative. In other words, Γ_j^g allows identifying the occupations that bring problems to the group ($\Gamma_j^g < 0$), whether these problems arise from the group's overrepresentation in bad occupations or underrepresentation in the good ones.

Analogously, we also single out the occupations in which the group is underpaid by looking at the occupations that contribute negatively to the value of Δ^g . Namely,

$$\Delta^g = \sum_j \underbrace{c_j^g (w_j^g - w_j)}_{\Delta_j^g} \frac{1}{C^g \bar{w}} = \sum_j \underbrace{\left(\frac{c_j^g}{C^g} \right)}_{\Delta_j^g} \left(\frac{w_j^g - w_j}{\bar{w}} \right). \quad (4)$$

We use these decompositions to identify from where the forfeits of deprived groups (i.e., those with wages below average) come as well as the gains of the advantaged ones.

Our analysis focuses on the counterfactual economy because it allows identifying patterns that would be hidden if the group's characteristics make it more or less likely that the group holds some occupations. Thus, for example, White women account for 30% of *lawyers, judges, and magistrates* in the actual economy, a representation equal to the group's share in the economy. Thus, White women are not underrepresented/overrepresented in this occupation. However, once we control for characteristics, their representation falls to 23.7%, which evidences the group's underrepresentation given its attributes. Analogously, Hispanic men are underrepresented among *physicians and surgeons* in the actual economy (they account for 3.9% of the occupation while representing 9.6% of total workers). However, after controlling for characteristics, there is a slight overrepresentation (they account for 10.5% of the jobs). In other words, taken into account the group's characteristics, they are not underrepresented there. The counterfactual analysis unveils the groups' underrepresentation/overrepresentation in occupations, and their underpayment/overpayment within them, beyond what is expected based on the groups' attributes.

Figures A1–A12 (see Appendix) highlight the occupations with the highest (absolute) values of Γ_j^g and Δ_j^g for each group in the exact counterfactual economy. If there were no differences in characteristics among our 12 gender–race/ethnicity groups, and if all the groups had the same opportunities in the labor market, the values of Γ_j^g and Δ_j^g would be close to zero. However, this is not what the charts depict.

We start our analysis by looking at what happens to female groups. *Physicians and surgeons, chief executives and legislators, managers nec* (not elsewhere classified), and *lawyers, judges, and magistrates* stand out as for having large negative values of Γ_j^g and Δ_j^g for most female groups (after controlling for attributes). In other words, the underrepresentation of most female groups in these highly-paid occupations ($\Gamma_j^g < 0$) and their underpayment within them ($\Delta_j^g < 0$) goes beyond women’s characteristics. A notable exception to this pattern are Asian women, given that they are not underrepresented among either *physicians and surgeons* (they are actually highly overrepresented) or *managers nec.*, and are not underpaid among *lawyers, judges, and magistrates*. However, Asian women are underpaid among *postsecondary teachers* and *sales representatives* and overrepresented in *personal appearance workers nec.*, beyond what would be expected based on their characteristics. Asian women also differ from other women with respect to *registered nurses*, a relatively well-paid, feminized occupation in which Asian women is the only female group with wages above the occupational wage.

Underpayment is also quite visible for all female groups among *first-line supervisors of sales workers, financial managers, and accountants and auditors. Retail salespersons and managers in marketing, advertising, and public relations* also show substantial underpayment for some female groups (especially, Black and Hispanic women in the former case and Native American women in the latter).²¹ On the other hand, underrepresentation in highly paid occupations also involves *software developers, applications, and systems software* for all female groups but Asians (although all women are underpaid there).

²¹ Black women’s underpayment in sales, healthcare, and management is also detected in Holder (2020) by using a different methodology, although our approach differs from hers given that we look not only at the wage penalties arising from underpayment, but also those stemming from underrepresentation in highly paid occupations and overrepresentation in low-paid ones.

Our counterfactual analysis also shows substantial overrepresentation for many female groups in low-paid jobs such as *cashiers* (a pattern shared by all female groups), *receptionists*, and *secretaries and administrative assistants*, which explains why these occupations have $\Gamma_j^g < 0$. Overrepresentation in *waiters and waitress* also involve many female groups, although not black women, who are instead overrepresented among *customer service representatives*, *personal care aides*, *maids and housekeeping cleaners* and, especially, *nursing, psychiatric, and home health aides* (Hispanic, Native American, and “other race” women also share overrepresentation in these occupations).

The reverse of the female situation is found in male groups, although not all of them are in the same situation. *Managers nec* is an occupation with overrepresentation and overpayment for all male groups except Blacks. *Chief executives and legislators* is an occupation in which all male groups except Blacks and Hispanics are overrepresented and all but Blacks, Native Americans, and “others” have wages above average. Overrepresentation is also dramatic among *lawyers, judges, and magistrates* for White men, who also earn wages above average, whereas Black and Native American men are underrepresented and underpaid in this occupation. The overrepresentation and overpayment of Hispanic, White, and especially Asian men among *physicians and surgeons* is also intense (on the contrary, Black and Native American men are underrepresented there, although not underpaid). *Software developers, applications and systems software* is also an occupation in which all male groups except Blacks and Native Americans are overrepresented (with overpayment for Whites and especially Asians). Among *first-line supervisors of sales workers*, all male groups except Blacks and Native Americans earn wages above average, although all of them seem to have an even representation. In *financial managers, accountants and auditors*, and *managers in marketing, advertising, and public relations* overpayment involves especially White and Asian men. Finally, in *retail salespersons*, overpayment affects especially White men.

The analysis suggests that most of the Black men’s earnings disadvantage arises not only from their underrepresentation/underpayment in the highly paid jobs mentioned above, but also from their overrepresentation in low-paid jobs: *janitors and building cleaners*, *laborers and freight, stock, and material movers*, *driver/sales workers and truck drivers*, *chefs and cooks*, and *security guards* (although in many of them they earn wages above average). The

overrepresentation of Hispanic and Native American men in these occupations is also significant, although they are overrepresented/overpaid in highly paid occupations in which their Black peers are not. A distinct pattern of Hispanic men is the overrepresentation and overpayment among *police officers and detectives* while that of Native American men is their overrepresentation and overpayment among *postsecondary teachers* and *petroleum, mining, and geological engineers* (which is a small occupation).

In what follows, we look at underpayment within occupations from a different angle, trying to quantify how many individuals underpayment in the counterfactual economy affects. Figure 6 shows, for each threshold on the horizontal axis, the proportion of individuals of the group having an underpayment within occupations equal or above that threshold. We find that underpayment is generalized among White women, given that it affects up to 96% of the group. Moreover, 23% of White women work in occupations in which their conditional wage is 10% or more below the occupational wage. However, unlike other female groups, their maximum wage gap within occupations does not surpass 38%. Native American women is the group not only with the highest penalty within occupations (their conditional wage can be up to 80% below the occupational wage), but also with the highest percentage of workers with penalties between 5% and 50% of the occupational wage. For example, in the counterfactual economy, about 50% of Native American women work in occupations in which their wage is at least 10% below the occupational wage, whereas in the same circumstances are 32%, 27%, 23%, and 14%, respectively, of Hispanic, Black, White, and Asian women.

The incidence of underpayment is lower for Black women than for White women (71% versus 96%), although the maximum intensity of underpayment is larger for Black women given that they can earn up to 70% below the occupational wage. The female group with the lowest incidence is that of Asians, given that underpayment affects only to 51% of them, although the maximum intensity of underpayment is higher for them than for White women.

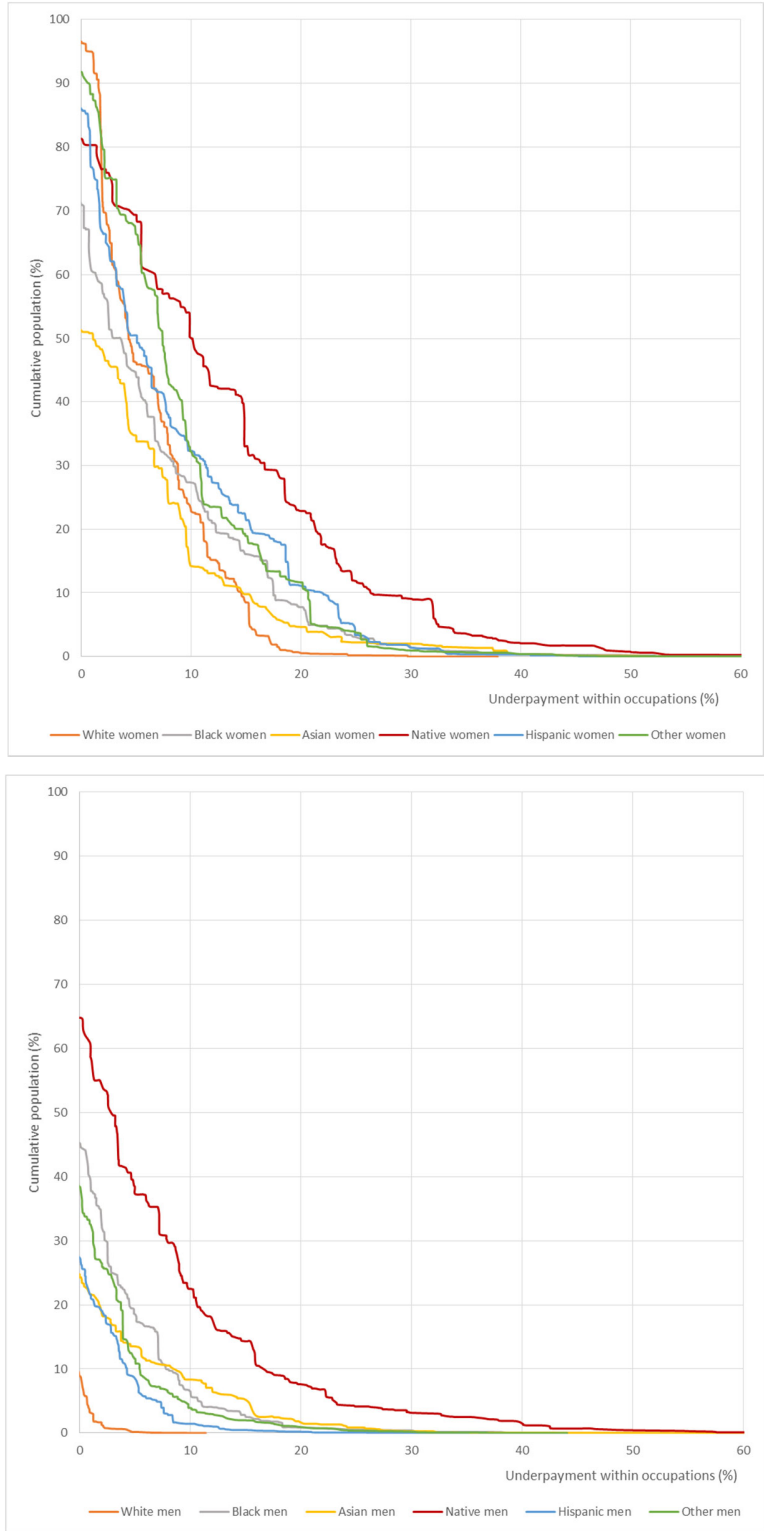


Figure 6. Cumulative population (%) by levels of underpayment within occupations (%) in the exact counterfactual wage distribution.

Native American men is the male group with the highest underpayment incidence (65% of the group works in occupations in which they earn less than other groups). However, this group's situation in the counterfactual economy is better than that of most female groups. Thus, for example, whereas 22% of Native American men have a wage penalty within occupations of 10% or more of the occupational wage, the percentage of White, Black, Hispanic, Native American, and "other race" women in this situation is larger (23–32%).

6. Conclusions

If gender and race/ethnicity did not privilege some groups and harm others, one would expect that groups that do not differ in terms of human capital, geographic location, and other basic characteristics would earn wages around the average. However, we find that some gender–race groups have conditional wages well above the average wage whereas others are clearly below. One could label a group in the first case as a privileged group and a group in the second as a deprived one. Therefore, the wage differential between these two groups could be disentangled into the premium of the former and the penalty of the latter, which brings a new perspective to what has been done in the literature that is based on pairwise comparisons (Antecol and Bedard, 2002, 2004; Greenman and Xie, 2007; Alon and Haberfeld, 2007; Blau and Kahn, 2017; Paul et al., 2018).

Our analysis reveals that the male advantage concentrates on two races, Asian and White, given that other male groups have conditional wages either below average (8% in the case of Black men) or around average (Hispanic, Native American, and "other race" men). Asian and White men, whose conditional wages are, respectively, 20% and 17% above the average, not only tend to concentrate in highly paid occupations beyond what would be expected as based on their characteristics, but also out-earn other groups within occupations. Black men is the only male group with conditional wages below average and also the only male group that tends to be concentrated in low-paid occupations after controlling for attributes. However, the male group that underpayment affects most within occupations is not Black but Native American men.

All female groups, except Asians, are deprived groups given that their conditional wages are clearly below average (11% in the case of White women and 18–21% for minority women).

White, Black, Hispanic, Native American, and “other race” women derive important wage disadvantages, after controlling for characteristics, due to both their occupational sorting and underpayment within occupations. Occupational segregation impacts especially Black women whereas underpayment within occupation affects especially Native American women (and to a higher extent than it does Native American men).

Our counterfactual analysis suggests that Asian women are neither a privileged nor a deprived group given that their adjusted wages are around average, which does not mean they do not suffer a gender penalty. In fact, Asian women have much lower wages than Asian men, a gap that does not seem to arise from Asian women having lower wages than expected, but from Asian men having larger ones. Unlike them, the gender gap of White women is the result of not only the large wages of White men, but also the low wages of White women. The fact that the gender wage gap of White women is larger than those of Black, Hispanic, and “other race” women does not stem from these minority women having larger conditional wages than White women do, but from their male peers having lower wages than White men do.

We have identified the occupations that strongly harm most female groups’ earnings after controlling for characteristics. These include: *management, business, science and arts* (especially due to female underrepresentation and underpayment among *managers nec* and *chief executives and legislators/public administration*, together with their underpayment among *financial managers*); *healthcare practitioners and technical* (especially *physicians and surgeons*, in which all female groups are underpaid and all but Asian women are also underrepresented); *computer and mathematical* (mainly due to the underrepresentation of all female groups except Asians among *software developers, applications and systems*, an occupation in which females are also underpaid); *sales and related* (mainly because of female underpayment among *first-line supervisors of sales workers* and their overrepresentation among *cashiers*); and *office and administrative support* (mainly arising from their overrepresentation as *secretaries and administrative assistants, receptionists, and customer service representatives* and female underpayment among *retail salespersons*). The concentration of Native American women, and especially, Black women in *healthcare support* (mainly *nursing, psychiatric, and home health aides*) also goes beyond what is expected based on the groups’ attributes. As for Black men, which is the only male group

with conditional wages below average, the main problem arises from their overrepresentation in *transportation and material moving (drivers/sales workers and truck drivers and laborers and freight, stock, and material movers)* and *building and grounds cleaning and maintenance (mainly janitors and building cleaners)*; their underrepresentation in *management, business, science and arts (mainly chief executives and legislators/public administration and managers nec, in which they are also underpaid)* and *healthcare practitioners and technical (especially physicians and surgeons)*; and their underpayment in *legal (lawyers, judges, and magistrates)*.

Our intersectional framework with 12 groups allowed us to picture the effect of gender and race/ethnicity more broadly than what the literature has shown thus far (Kilbourne et al., 1994; Kim, 2009; Paul et al., 2018). Unlike Green and Xie (2008), we have delved not only on racial variation on the gender wage gap, but also on wage differentials between women and men who belong to different races. Although there is no single gender penalty, which is consistent with literature based on regression models (Green and Xie, 2008; Paul et al., 2008), making use of our counterfactual economy, we have documented that gender penalizes more than race. White women's gender penalty is much larger than the racial penalty of any male (or female) group, which explains why White women earn lower wages than any male group with similar characteristics. Moreover, given that Black, Hispanic, Native American, and "other race" women are penalized with respect to their White peers (although less than racial-minority men are), these groups also receive lower earnings than any male group with similar characteristics (regardless of their race/ethnicity). These minority women's gender penalties are also larger than their racial penalties. As for Asian women, they have lower adjusted earnings than any male group except Native Americans, whose earnings are similar to theirs, and Blacks. Moreover, although Black men fare worse than comparable men of any other race/ethnicity, they fare better than White, Black, Hispanic, Native American, and "other race" women of similar characteristics. All this suggests that if all groups had the same characteristics, the labor market would relegate women to the bottom of the wage ladder.

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Appendix

Building the Exact and Semiparametric Counterfactuals

Let $z \equiv (z_1, \dots, z_k)$ denote the vector of the k covariates describing the attributes of each subgroup or cell, and let $Group$ be a dummy variable indicating group membership. To streamline the presentation, we explain how to build the counterfactual distribution for only one group, Black men ($Group = BM$), although the same procedure has to be followed for the other groups as well.

If we represent by $F(w, o, z | Group = BM)$ the joint distribution of wages, occupations, and attributes for Black men, its discrete density function can be written as:

$$\begin{aligned}
f(w, o | \text{Group} = BM) &= \int_z dF(w, o, z | \text{Group} = BM) dz = \\
&= \int_z f(w, o | z, \text{Group} = BM) f(z | \text{Group} = BM) dz
\end{aligned}$$

where $f(w, o | z, \text{Group} = BM)$ is the distribution across wages and occupations of Black men having attributes z , and $f(z | \text{Group} = BM)$ is the attribute density for Black men. If we assume that the distribution of individuals in each cell does not depend on the distribution of attributes (i.e., if $f(w, o | z, \text{Group} = BM)$ and $f(z | \text{Group} = BM)$ are independent), then we can define the counterfactual density function of Black men as the density function they would have were they given the distribution of White men's attributes (i.e., $f(z | \text{Group} = WM)$), whereas keeping unchanged the distribution of every subgroup across occupations (i.e., $f(w, o | z, \text{Group} = BM)$). Namely, the counterfactual distribution for Black men is

$$\tilde{f}_{BM}(w, o) = \int_z f(w, o | z, \text{Group} = BM) \cdot f(z | \text{Group} = WM) dz . \quad (\text{A1})$$

By defining the reweighting function

$$\Psi_z = \frac{f(z | \text{Group} = WM)}{f(z | \text{Group} = BM)} \quad (\text{A2})$$

and taking into account that $f(w, o, z | \text{Group} = BM) = f(w, o | z, \text{Group} = BM) \cdot f(z | \text{Group} = BM)$, we can re-formulate expression (A1) as follows:

$$\tilde{f}_{BM}(w, o) = \int_z \Psi_z \cdot f(w, o, z | \text{Group} = BM) dz . \quad (\text{A3})$$

In other words, to calculate the counterfactual distribution, each Black male individual is reweighted according to the quotient of frequencies between individuals with those characteristics among White and Black men ($f(z | \text{Group} = WM)$ and $f(z | \text{Group} = BM)$, respectively).

After doing this process for all gender–race/ethnicity groups, we build a counterfactual economy in which all these groups no longer differ in terms of observed characteristics because all of them have the same characteristics as White men. We call this the exact counterfactual.

Following DiNardo et al. (1996) and Gradín (2013), we also build another counterfactual, which we call the “semiparametric” counterfactual, where the reweighting scheme is obtained in a different way. Using Bayes’ theorem, Ψ_z can be expressed as

$$\Psi_z = \frac{\Pr(\text{Group} = BM) \Pr(\text{Group} = WM | z)}{\Pr(\text{Group} = WM) \Pr(\text{Group} = BM | z)}. \quad (\text{A4})$$

The first term of the above expression can be approximated by the ratio of the Black men’s population to White men’s population in the sample. The second term can be estimated calculating the probability of an individual with attributes z being White men rather than Black men using a logit model over the pooled sample of observations from both groups:

$$\Pr(\text{Group} = WM | z) = \frac{\exp(z\hat{\beta})}{1 + \exp(z\hat{\beta})}, \quad (\text{A5})$$

where $\hat{\beta}$ is the associated vector of estimated coefficients. The same procedure would have to be followed for the remaining gender–race/ethnicity groups.

This method is useful to determine each factor’s contribution to the difference between the *EGap*’s conditional and unconditional values. To obtain, for example, the contribution of education, we calculate the prediction of $\Pr(\text{Group} = WM | z)$ by assuming that all coefficients in the logit model except for those of education dummies are zero; then we compare the *EGap* of Black men in the counterfactual to the *EGap* in the actual distribution. This would represent the contribution of education if this were the first variable for which we account. Then, we calculate the prediction while assuming zero coefficients for all covariates except for education and one other covariate, e.g., age. The resulting counterfactual is compared to the counterfactual where only age is taken into account. The analysis is repeated with immigration profile as the other covariate accounted for, and so on. This allows determining the marginal contribution of education when this is the second factor for which we control. We continue by following the same procedure while considering all possible sequences where education is the third, rather than the second, factor to change and so on. Finally, we average over all possible marginal contributions of education.

Tables and Graphs

Table A1. Basic characteristics of the gender–race/ethnicity groups

	White men	Black men	Asian men	Native A. men	Hispanic men	Other men	White women	Black women	Asian women	Native A. women	Hispanic women	Other women	Total
Number of observations	2,394,843	255,549	201,310	22,203	498,062	64,124	2,203,174	321,301	193,931	24,000	426,043	64,242	6,668,782
Population share (%)	32.81	5.36	3.14	0.26	9.60	1.06	29.73	6.30	2.91	0.27	7.51	1.04	100
Education attainment (%)													
Less than high school	5.77	8.53	7.76	11.74	28.02	8.41	4.28	6.99	8.32	8.65	18.89	6.86	8.87
High school diploma	25.84	33.43	13.61	35.62	30.91	23.89	20.55	25.29	13.74	26.98	26.64	18.09	24.38
Some college	30.94	35.67	19.76	36.22	26.30	34.51	33.26	39.31	20.86	43.23	33.20	36.99	31.64
Bachelor's degree	24.17	14.94	30.46	11.48	10.37	21.65	26.10	17.47	33.53	13.90	14.74	24.31	22.18
Master's or doctoral degree	13.27	7.43	28.41	4.94	4.40	11.55	15.81	10.94	23.54	7.23	6.53	13.75	12.93
Years of residence (%)													
US born	94.54	84.03	22.67	97.45	46.57	79.84	95.10	86.43	22.95	97.7	54.81	82.14	81.43
Living <=15 years	1.81	7.29	34.35	0.76	19.30	7.79	1.49	5.71	31.86	0.78	15.06	6.17	6.93
Living >15 years	3.65	8.68	42.99	1.79	34.13	12.37	3.41	7.86	45.19	1.52	30.13	11.69	11.64
English proficiency (%)													
Only English or well/very well	99.59	99.10	89.92	99.54	80.21	98.46	99.69	99.09	88.81	99.58	84.38	98.80	95.92
Not well or not at all	0.41	0.90	10.08	0.46	19.79	1.54	0.31	0.91	11.19	0.42	15.62	1.20	4.08
Age (%)													
Young(<=35)	35.34	42.06	38.38	41.70	46.34	54.15	35.5	40.32	37.24	39.25	47.13	54.54	38.58
Middle-aged(36-55)	41.70	41.83	45.66	41.50	42.45	35.58	41.33	42.89	46.41	41.79	41.49	35.03	41.85
Older(>=56)	22.96	16.12	15.96	16.80	11.21	10.27	23.16	16.79	16.34	18.96	11.38	10.43	19.56

(Table continued below.)

Table A1, continued. Basic characteristics of the gender–race/ethnicity groups

	White men	Black men	Asian men	Native A. men	Hispanic men	Other men	White women	Black women	Asian women	Native A. women	Hispanic women	Other women	Total
Metropolitan area size (%)													
Area < 1 million people	49.13	31.91	19.75	70.24	31.04	38.99	49.56	31.30	20.51	71.94	30.78	39.07	42.25
Area >= 1 million people	50.87	68.09	80.25	29.76	68.96	61.01	50.44	68.70	79.49	28.06	69.22	60.93	57.75
Region of residence (%)													
Northeast	18.90	15.69	20.10	4.89	13.46	15.47	19.83	15.83	19.41	4.47	14.65	16.12	17.88
Midwest	26.95	16.44	12.79	17.14	9.45	17.12	27.49	16.79	11.79	16.66	9.23	17.32	21.75
South	34.47	58.35	23.70	35.27	38.14	32.34	33.88	59.59	22.90	33.60	36.94	32.81	36.98
West	19.69	9.52	43.41	42.70	38.95	35.07	18.80	7.78	45.89	45.28	39.17	33.74	23.39
Part-time work (%)													
Working < 35 hours	12.86	16.18	12.37	14.31	12.82	18.80	26.22	21.97	22.69	23.29	26.80	29.41	19.16
Working >= 35 hours	87.14	83.82	87.63	85.69	87.18	81.20	73.78	78.03	77.31	76.71	73.20	70.59	80.84
Children (%)													
No children (<= 15 years)	71.61	74.74	65.03	70.74	65.78	71.59	71.71	67.36	67.48	66.64	62.49	69.60	69.93
Children (<= 15 years)	28.39	25.26	34.97	29.26	34.22	28.41	28.29	32.64	32.52	33.36	37.51	30.40	30.07
Living with a partner (%)													
No partner	35.41	53.26	35.93	46.57	45.04	49.78	39.42	67.16	38.16	52.15	52.36	55.39	42.29
Partner	64.59	46.74	64.07	53.43	54.96	50.22	60.58	32.84	61.84	47.85	47.64	44.61	57.71

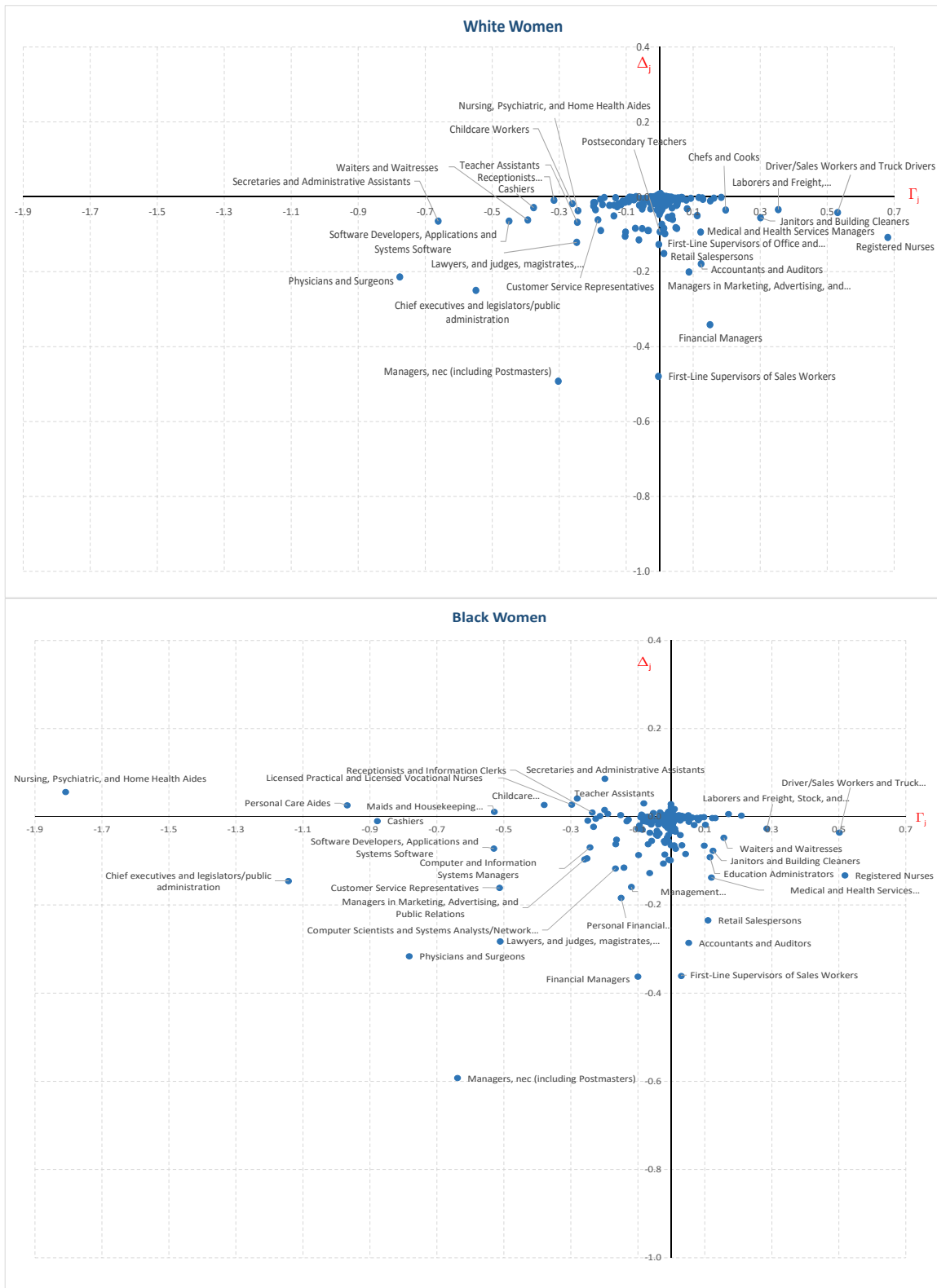


Figure A1. Occupations with the highest (absolute) values of Γ_j^g and/or Δ_j^g for each group in the exact counterfactual wage distribution (continued on next page).

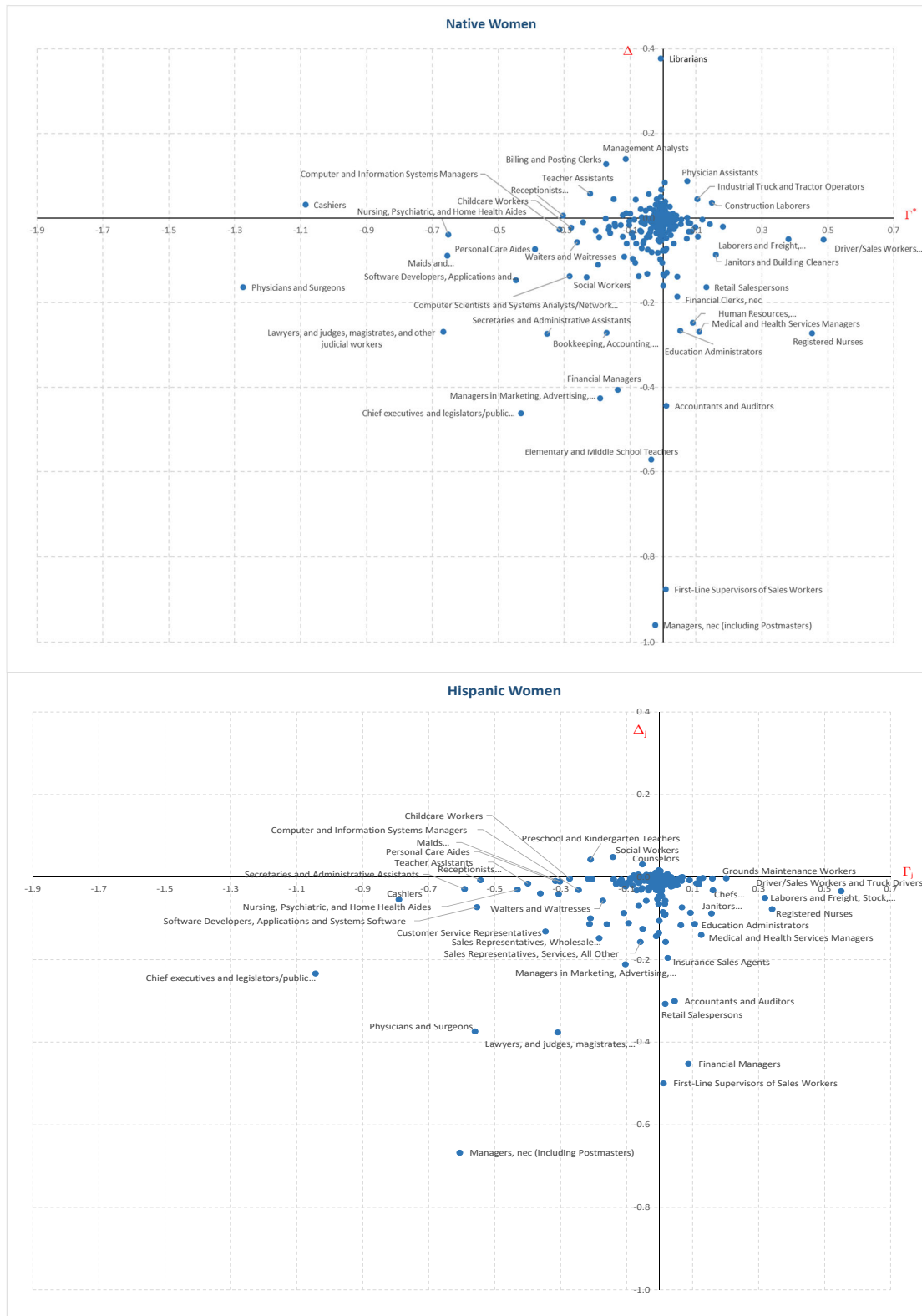


Figure A1. Occupations with the highest (absolute) values of Γ_j^g and/or Δ_j^g for each group in the exact counterfactual wage distribution (continued on next page).

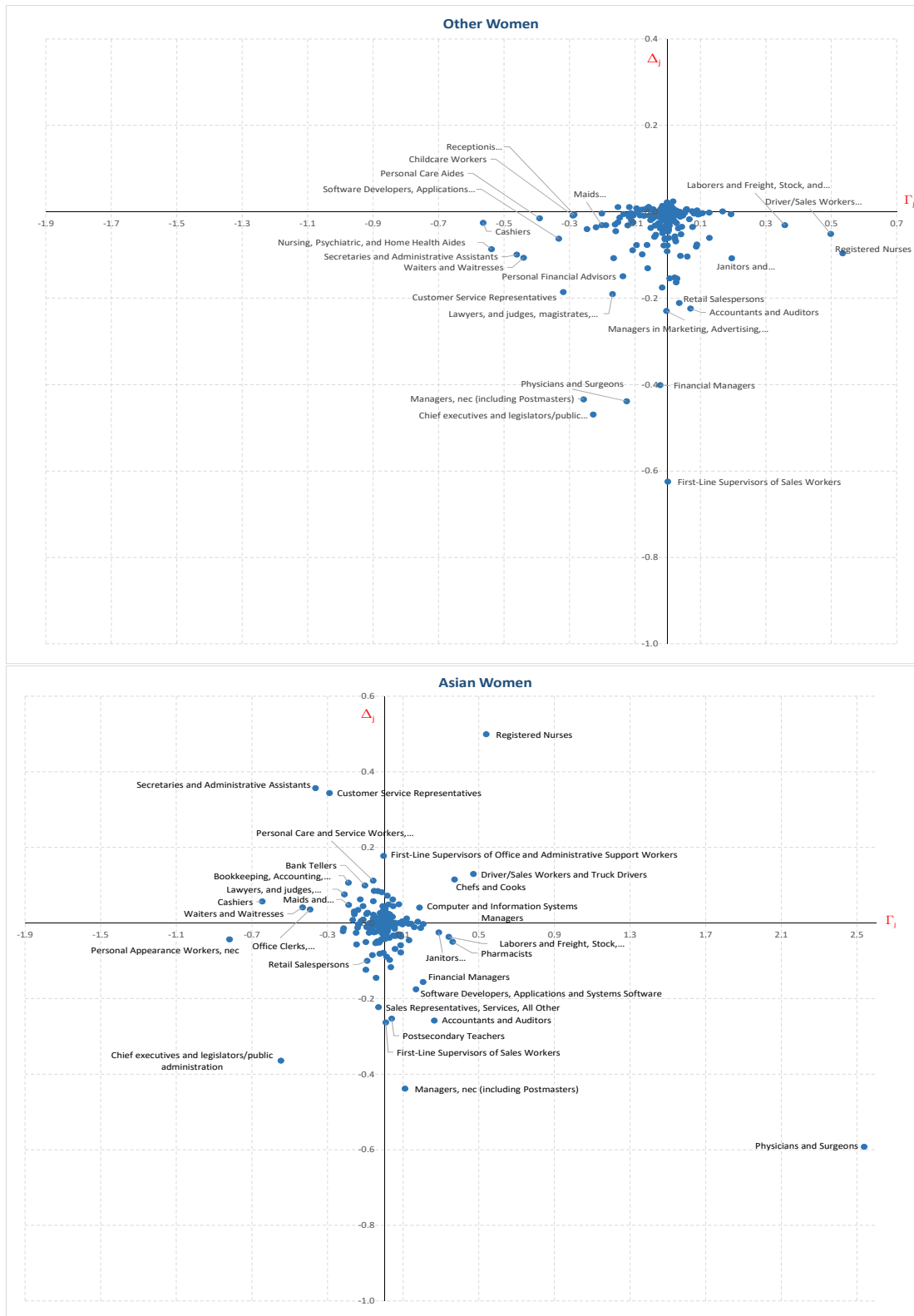


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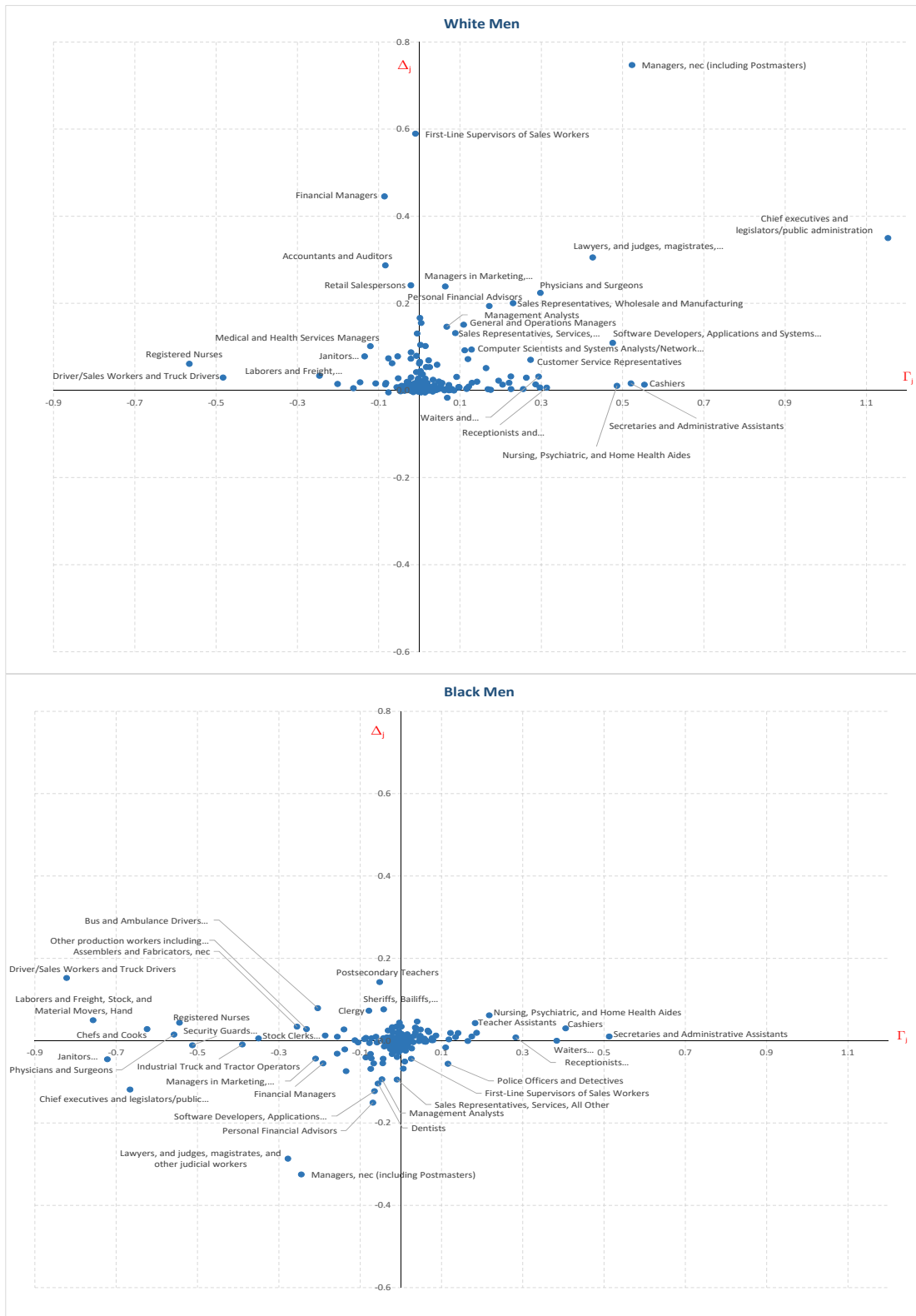


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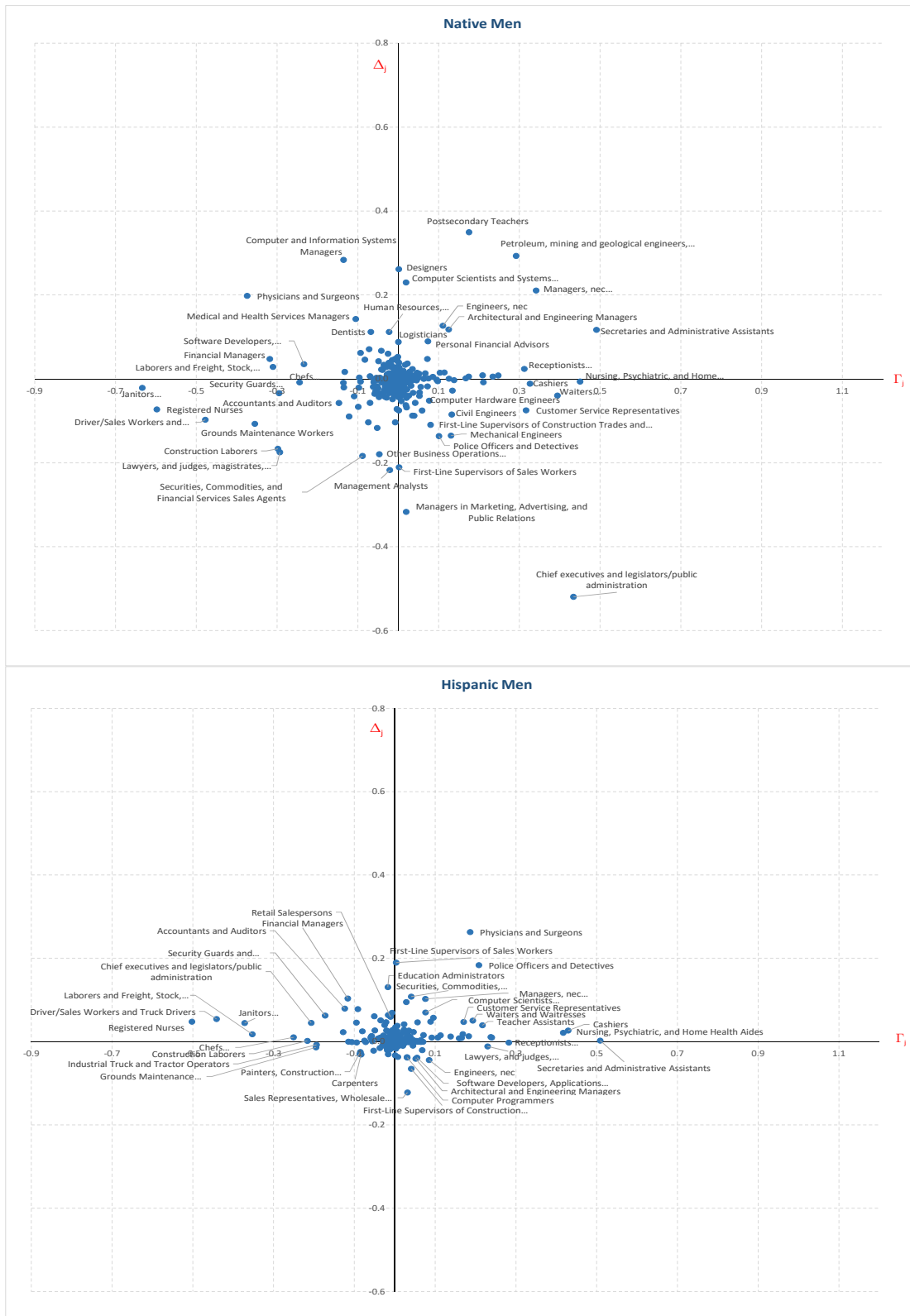


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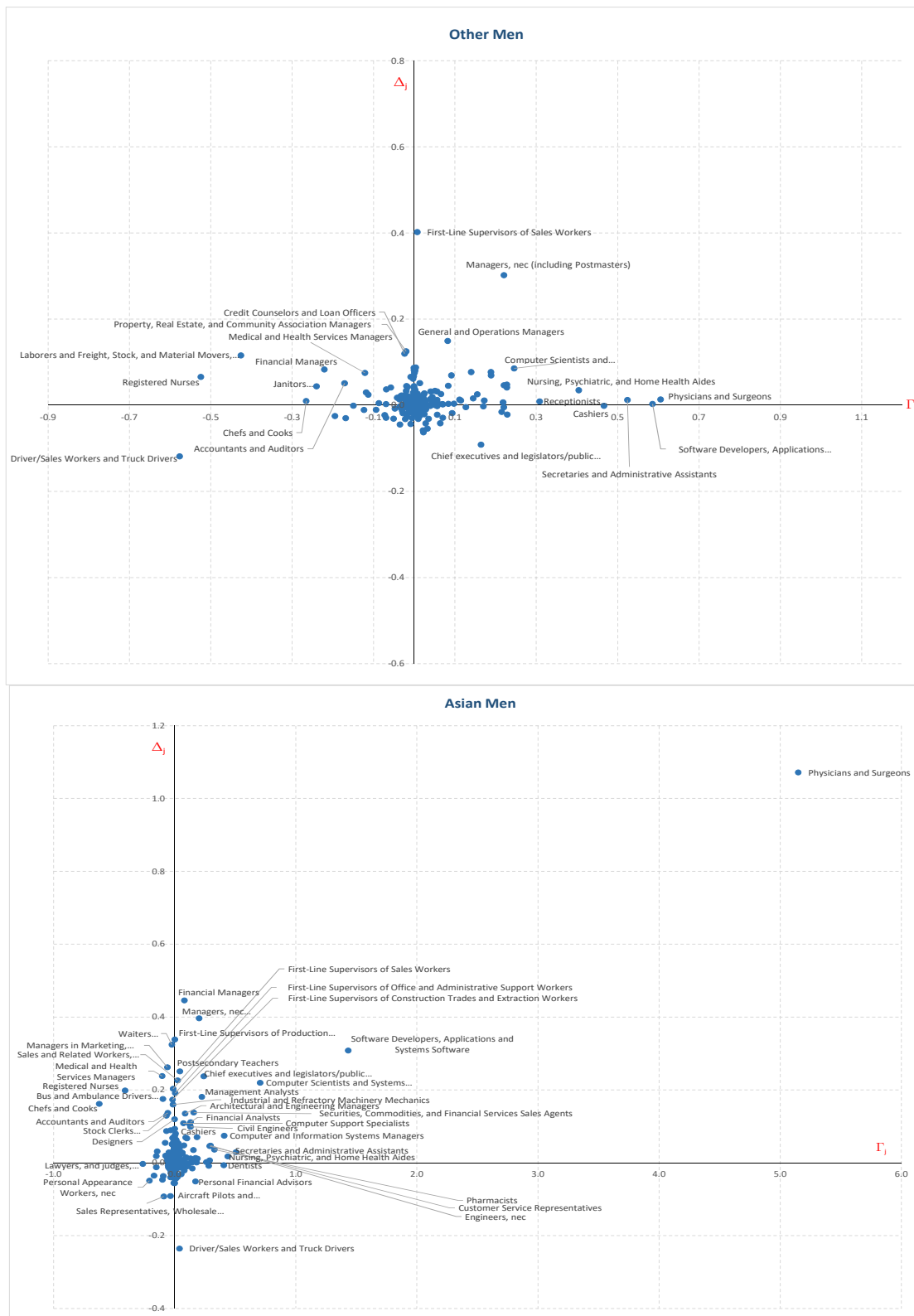


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