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Gender and Race/Ethnicity: An Intersectional Framework
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Privilege and Hindrance on the U.S. Earnings Distribution by Gender and Race/Ethnicity: An Intersectional Framework with 12 Groups*

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Abstract

If gender and race/ethnicity did not privilege some groups and harm others, one would expect that groups that do not differ in 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. We label a group in the first case as a privileged group and a group in the second as a deprived one. The wage differential between these two groups can 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 based on pairwise comparisons. Our intersectional framework 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.

JEL Classification: D63; J15; J16; J71

Keywords: Earnings, 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, 2005; Greenman and Xie, 2008; Mandel and Semyonov, 2016; Paul et al., 2021).

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., 2021). 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? Do all female groups have conditional wages below average? How do Native American women fare compared to similar Black or Hispanic women. 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 using a methodology that allows us to examine the above groups

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

jointly, 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 method 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.

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 in that cell unaltered. Wage 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, bringing a new perspective to what has been done in the literature based on pairwise comparisons.

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. Section 5 offers the main conclusions.

2. Background

2.1 Previous Findings

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).² 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., 2021).³ 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., 2021). As for White women, the literature indicates

² 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.

³ Some argue that the racial penalty would disappear if instead AFQT (Armed Forces Qualifying Test) scores were used, a matter not free of controversy.

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., 2021).

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. (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, but it does not explain the gender wage gaps of White, Black, and Hispanic women (Trejo, 1997; England et al., 1999; Antecol and Bedard, 2004; Duncan et al., 2006; Patten, 2016; Paul et al., 2021). 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., 2021). 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; Budig et al., 2021).⁴ The fact that these studies encompass different target populations,⁵ 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.

⁴ 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.

⁵ 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).

3. Data and Methodology

Our data come from the 2015–2019 five-year sample of the American Community Survey provided by the Integrated Public Use Microdata Series (Ruggles et al., 2020). We partition the population into 12 gender–race/ethnicity groups, which result from considering women and men of six racial/ethnic groups: Hispanics (irrespective of race), non-Hispanic Whites, Blacks, Asians, Native Americans, and “other races” (non-Hispanics that self-report some other race or more than one race). To determine each group’s wages, we trim the tails of the hourly wage distribution (wages below the 1st percentile or above the 99th percentile of positive values in each occupation). The final sample comprises 6,668,782 workers.

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 control variables are: education achievements, age, years of residence in the U.S., English proficiency, metropolitan area size, region of residence, part-time work, children, and living with a partner.⁶ Table A1 in the Appendix provides the characteristics of the groups.⁷

To build the “exact” counterfactual, we split each group into subgroups or “cells” that result from specific combinations of our covariates (e.g., having a Bachelor’s degree, 30 to 54 years of age, U.S. born, 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 keep these individuals’ wages unaltered, but we change the weight that each cell has in the group to make it equal to that of White men with the same characteristics.

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. We explain how to define the weighting scheme for only one group, Black men ($Group = BM$), although the same procedure has to be followed for the other groups as well.

⁶ We do not control for occupation and/or sector because the sorting of workers across these categories is not a gender- and race-blind process (Blau and Ferber, 1984; Reskin and Cassirer, 1996; Reskin and Bielby, 2005; Del Río and Alonso-Villar, 2015; Blau and Kahn, 2017).

⁷ Taking into account the number of observations of some of the gender–race groups in the sample, we opt for not increasing the number of categories considered in the analysis.

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: $\Psi_z = \frac{f(z|Group = WM)}{f(z|Group = BM)}$. 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). In this case, $\Psi_z = \frac{\Pr(Group = BM)}{\Pr(Group = WM)} \frac{\Pr(Group = WM|z)}{\Pr(Group = BM|z)}$. The first term is approximated by the quotient of frequencies of the corresponding groups and the second term requires estimating $\Pr(Group = WM|z)$ using a logit model over the pooled sample of observations from both groups (note that $\Pr(Group = BM|z) = 1 - \Pr(Group = WM|z)$).

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 of factors, thus improving DiNardo and coauthors method (see Appendix). 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.

Following Del Río and Alonso-Villar (2015), a group’s earnings gap, $EGap$, is defined as the differential between the group’s average wage and the economy’s average wage divided by the latter. By calculating the $EGap$ of each group in the counterfactual economy, we can compare the conditional earnings of our 12 groups simultaneously, which makes this approach especially convenient for disentangling the effects of gender and race/ethnicity in an intersectional framework.

4. Wages 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 using the actual wage distribution. 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.

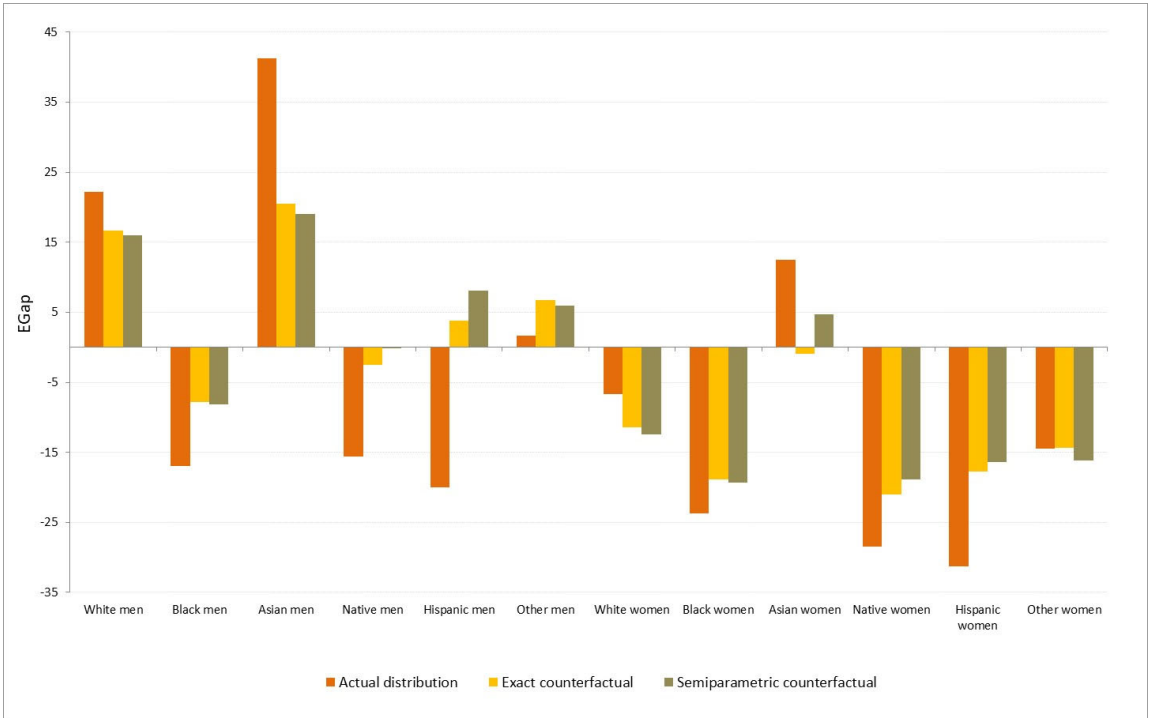


Figure 1. The earnings gap (*EGap*) of each group (with respect to average wage) in the actual and counterfactual distributions.

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.⁸

4.1 The Exact Counterfactual

To account for differences in composition, first, we build the exact counterfactual wage distribution. This counterfactual analysis is also provided in Figure 1.⁹ 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. 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. 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).¹⁰

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 clearly 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., 2021), although our analysis takes a step further documenting and quantifying Black men's wage

⁸ Intergroup wage disparities are larger now than a decade ago (Del Río and Alonso-Villar, 2015), in part due to Asians' wages rising.

⁹ 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.

¹⁰ 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. 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 a joint category that includes master and bachelor's degree is additionally split into STEM (Science, Technology, Engineering, and Mathematics) and non-STEM studies also suggests that Asian men out-earn White men.

disadvantage with respect to Asian, Hispanic, Native American, and “other race” men (28%, 12%, 5%, and 15%, respectively).



Figure 1 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). 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)¹¹ and is the fact that female groups’ earnings are lower than those of their same-race male peers (Paul et al., 2021; 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.¹²

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 sum of a gender and a racial penalty (or premium) using a consistent sequence of

¹¹ The advantage of Asians vis-à-vis Whites 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.

¹² 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.

comparisons. Figure 2 provides the gender, racial, and gender–race earnings gaps of the groups (obtained from Figure 1).

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.¹³

¹³ Our reasoning follows Del Río and Alonso-Villar (2019), who explore the sexual orientation wage gap of racial minority women and men.



Figure 2. *EGap* differentials among gender-race/ethnicity groups in the exact counterfactual wage distribution.

Notice that our approach differs from Kim (2009) and Paul et al. (2021) 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 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 2 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.¹⁴

¹⁴ These results are consistent 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 fewer controls, and Paul et al. (2021), who study only Black and White workers.

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 1). 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 than in the exact counterfactual. For the other gender–race/ethnicity groups, the estimated wages barely change between the two counterfactuals.

Figure 3 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.

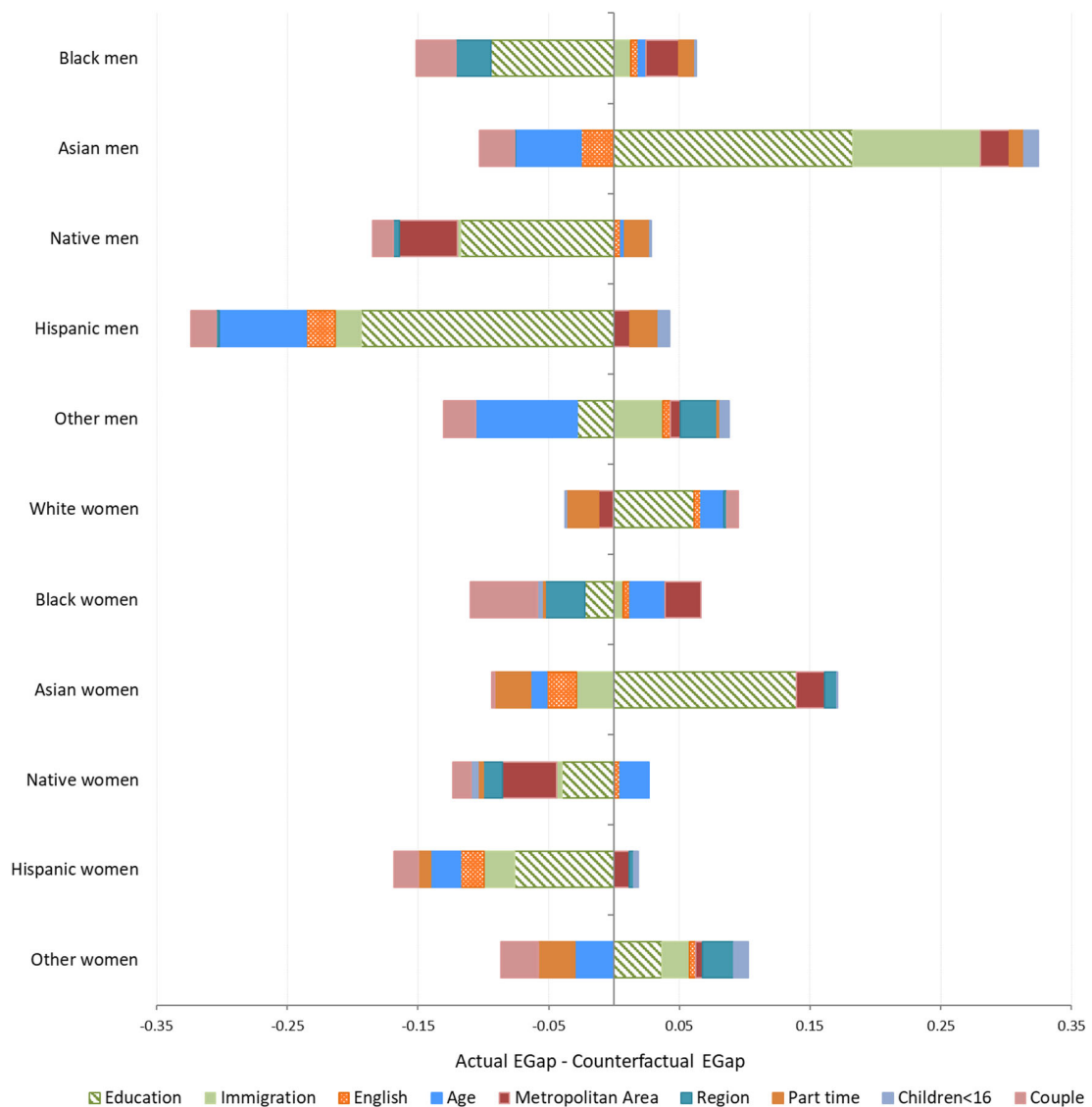


Figure 3. Actual *EGap* minus semiparametric counterfactual *EGap* and factors' contributions.

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.¹⁵ 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.¹⁶ 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). 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.¹⁷

¹⁵ 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.

¹⁶ This is consistent 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.

¹⁷ 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.

“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, “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.¹⁸ 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. 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., 2021).

Our analysis reveals that only Hispanic men, Native American men, and Asian women have conditional wages around average. Black men and, especially, White, Black, Hispanic, Native American, and “other race” women have conditional wages clearly below average, whereas those of Asian and White men are well above average. 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

¹⁸ 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.

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.

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., 2021). Unlike Greenman 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 (Greenman and Xie, 2008; Paul et al., 2021), 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

To streamline the presentation, we explain how to obtain the reweighting scheme for only one group, Black men ($Group = BM$). If we represent by $F(w, z | Group = BM)$ the joint distribution of wages and attributes for Black men, its discrete density function can be written as:

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

where $f(w|z, Group = BM)$ is the distribution across wages of Black men having attributes z , and $f(z|Group = BM)$ 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 $f(w|z, Group = BM)$ and $f(z|Group = BM)$ 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., $f(z|Group = WM)$), whereas keeping unchanged the earnings distribution of every subgroup (i.e., $f(w|z, Group = BM)$). Namely, the counterfactual distribution for Black men is

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

By defining the reweighting function

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

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

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

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 ($f(z|Group = WM)$ and $f(z|Group = BM)$, 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

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

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:

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

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 $\Pr(\text{Group} = \text{WM} | z)$ 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.

Table

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