Expansion, Diversity, and Choice:
Wage Inequality among College-Educated Workers, 1960-2016[1]

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Research on returns to higher education typically focuses on the college premium, or inequalities between workers who have a college degree versus those who do not. Yet, this focus on the college premium necessarily overlooks inequalities *within* the population of college-educated workers. In this article, we use 17 waves of Census and American Community Survey (ACS) microdata spanning from 1960 to 2017 to assess wage inequality among native-born college workers. We use unique regression techniques that examine inequality, and also decompose sources of inequality, across the entire wage distribution. We find that bachelor's degree-holders account for most of the wage inequality among U.S. workers as a whole. Within-college inequality has accelerated in recent years, and contributes as much to total inequality trends as the college premium. We further find the emergence of a broadly-shared wage gap over time, with high-wage men, white workers, and Asian workers distancing themselves from all other groups. Although major choice is commonly advanced as a way for students to have some say over their eventual wages, we find that major choice is unable to close inequalities tied to gender and race/ethnicity, particularly at the top of the wage distribution. These findings support a structurally-based, rather than an agentic-based, model of wage inequality among college-educated workers, which is often de-emphasized in studies of returns to higher education. Implications for research on stratification and higher education are discussed.

Keywords: inequality, higher education, returns to education, gender, race, major choice

How unequal are college graduates' wages? Past research on returns to education has focused mostly on the economic value of a college degree—what is often called the "college premium" because it refers to the additional earnings associated with the completion of a bachelor's degree, over and above lower levels of education. Recent estimates indicate that the college premium is substantial and has grown over time (Autor 2014; Autor, Katz, and Kearney 2008; Carnevale, Rose, and Cheah 2014; Fischer and Hout 2006; Goldin and Katz 2008; Tamborini, Kim, and Sakamoto 2015; Torche 2011). But although gaps have widened between college and non-college workers (what economists often refer to as "skilled" and "unskilled" workers (Altonji et al. 2016)), this trend has occurred alongside substantial changes to the population of college-educated workers in terms of both size and diversity (Brand and Xie 2010; DiPrete and Buchmann 2013; Horowitz 2018; Hout 2012; Schofer and Meyer 2005). Thus, while most scholars have focused on inequality *between* levels of education, inequality *within* levels of education—and specifically among college-educated workers—may be equally important to total inequality trends.

To the extent that wages among college graduates are unequal, prior research highlights two main reasons why this may be the case. The first is that college graduates earn different wages on account of their ascriptive characteristics, such as gender and race/ethnicity.[2] Although college-educated workers are collectively described as "skilled," and their wages are assumed to be enhanced relative to those with less education, social scientists have repeatedly shown that women and people of color are perceived as less skilled than their men and white counterparts (Correll, Benard, and Paik 2007; Moss and Tilly 1996, 2001; Ridgeway 2011). Accordingly,

[2] Throughout this article, we refer to gender and race/ethnicity as "ascriptive characteristics," with the understanding that other characteristics may also predict a college graduate's earnings.

college-educated workers with different ascriptive characteristics may have different wages despite equivalent credentials. This is a trend that may have intensified over the past several decades, as the population of college-educated workers has diversified, and competition for high-wage jobs has increased.

The second potential source of wage inequality is major choice, which scholars have recently focused on as a persistent source of stratification throughout the life course. Students who graduate in different majors can expect to earn different wages, and these wage differences are often assumed to reflect the skills of the students and the complexity of the knowledge gained (Altonji et al. 2016; Kim, Tamborini, and Sakamoto 2015; Rumberger and Thomas 1993). These two perspectives reflect different sources of inequality—ascriptive characteristics being a more *structural* source of inequality because gender and race reflect durable advantages and disadvantages that are embedded in social life, and major choice being a more *agentic* source of inequality because it implies some degree of individual decision-making and personal control over labor market outcomes. But, to what extent can major choice alleviate inequality on account of gender and race/ethnicity? That is, can agency overcome structural sources of inequality among college-educated workers?

In this article, we ask the following questions: (1) How unequal are college graduates' wages today, and how has this inequality changed over time? (2) How do college graduates' wages vary by gender and race/ethnicity? (3) And, to the extent that we observe gender and racial/ethnic wage gaps, can major choice alleviate these ascriptive sources of inequality? We answer these questions using 17 waves of Census and American Community Survey (ACS) microdata, which are ideal for our analyses because they include fine-grained data on wages and ascriptive categories. Detailed data on college majors are available for the 2009-2017 waves of the ACS, which we use to compare wage inequalities on account of major choice and gender-race/ethnicity. Overall, we find that bachelor's degree-holders account for most of the total wage inequality among U.S. workers. This trend has accelerated since 1990, and especially since the Great Recession. We further find that although changes in wage inequality have been uneven across social groups, much action has occurred at the top of the wage distribution, and high-wage men, whites, and Asians have distanced themselves from all other college graduates. In addition, although college majors have been shown to be tied to large wage gaps on their own, we find that major choice is unable is alleviate the inequality we find at the top of the wage distribution, which is driving inequality among college workers as a whole. We contend that these findings support a structurally-based, rather than an agentic-based, model of wage inequality among college-educated workers, which is often de-emphasized in studies of returns to higher education.

BACKGROUND

Wage Inequality among College-Educated Workers

The economic value of a college degree has received increased attention in recent years. As tuition and fees have increased, and many families have taken on substantial loans to cover students' college costs (Dwyer, McCloud, and Hodson 2012; Houle 2014; Quadlin and Rudel 2015), universities—and, indeed, higher education as an enterprise—has been under greater scrutiny to demonstrate that college degrees pay off in the long run (Chetty et al. 2017; Hurwitz and Smith 2018; Powell 2016). Although many critics have questioned whether college is a sound financial investment in today's economy, most studies show that bachelor's degrees generally carry a considerable premium. Recent estimates indicate that college graduates who work full-time from ages 25 to 64 earn an average of $2.8 million more than their counterparts with only a high school diploma (Carnevale et al. 2014). What is more, the size of the college premium has grown over time (Autor 2014). As of 2013, those with college degrees made approximately 98 percent more per hour than those without a degree, versus 85 percent in the 2000s, and 64 percent in the early 1980s (Carnevale et al. 2014). This evidence suggests that the average worker can expect substantial economic returns to higher education over the course of a lifetime.

Although the average returns to a college degree are well-documented, less research has been devoted to differences in returns among those with college degrees. In other words, studies have often focused on differences *between* levels of education, or between "skilled" and "unskilled" workers in economic parlance, with less attention paid to differences *within* the college-educated workforce (but see Brand and Xie 2010; Deming 2018; Kim, Tamborini, and Sakamoto 2015). As scholars of stratification have frequently argued, inequality occurs not only between groups, but also within observable social categories that social scientists investigate at the individual level—often referred to as "within-group inequality" (DiNardo, Fortin, and Lemieux 1996; McCall 2000; VanHeuvelen 2018a, 2018b, 2018c; Western, Percheski, and Bloome 2008). The rapid expansion of the college-educated workforce, in particular, suggests that this group would experience substantial within-group inequality, as bachelor's degree-holders now comprise nearly one-third of U.S. workers. The broadly shared expansion of college education indicates that contemporary college-educated workers are necessarily more diverse and varied than those in previous generations. Moreover, this group is largely inclusive of the high wage-earners who are driving contemporary inequality—a dynamic we will return to throughout this article.

In this article, we focus on two factors that we hypothesize as creating within-group inequality in the population of college-educated workers: ascriptive characteristics (i.e., gender, race/ethnicity) and college major. Further, we assess their relative contributions to inequality among college graduates, essentially assessing whether agentic sources of inequality can overcome structural sources of inequality within this segment of the labor market.

Gender, Race/Ethnicity, and Inequality among College Graduates

Research that has focused on inequality among college graduates shows that gender and race/ethnicity are associated with substantial earnings differentials (Buchmann and DiPrete 2006; Kim and Sakamoto 2017). Much of these earnings differentials are attributable to factors that are correlated with people's social categories; for example, college students with different ascriptive characteristics (most notably gender) sort into different majors that are, in turn, associated with different earnings (Charles and Bradley 2009; England and Li 2006; Jacobs 1996)—a mechanism we explore in depth in the analyses. College students in different ascriptive groups may also attend different types of institutions whose degrees carry different value in the labor market (Goldrick-Rab 2006)—a mechanism we are unable to analyze using ACS data, but that we consider further in the discussion section. But even experimental studies that explicitly isolate the effects of ascriptive characteristics show that college graduates in disadvantaged social groups, but who are otherwise similar to their more advantaged peers, have relatively poor labor market outcomes (Gaddis 2015; Deming et al. 2016; Quadlin 2018). These poor labor market outcomes are often tied to the widespread perception that members of disadvantaged groups have relatively poor skills and abilities, regardless of their credentials (Correll et al. 2007; Moss and Tilly 1996, 2001; Ridgeway 2011).

The economic returns for college graduates in disadvantaged social groups are becoming increasingly relevant, as these groups make up a larger percentage of bachelor's degree-holders than in previous decades. These demographic shifts come on the heels of a wide range of policies (e.g., financial aid, affirmative action) as well as advocacy efforts intended to expand access to higher education for women and people of color (Baker and Vélez 1996; Kao and Thompson 2003). Figure 1 shows our calculations of how the demographics of college-educated workers have shifted over time with respect to gender, race/ethnicity, and nativity. Although we do not focus on nativity pay gaps in this article, we include immigrants in Figure 1 to show how the entire population of college-educated workers (both native-born workers and immigrant workers) has changed over time.

(Figure 1 about here)

As shown in Figure 1, in 1960, white native-born men comprised more than three-fifths of the college-educated workforce. If we broaden this group to include women, nearly 90 percent of the college-educated workforce was white and native-born. These demographics have changed substantially in the intervening 50 years. White native-born men declined from 60 percent to 30 percent, and white native-born women increased from 25 percent to 37 percent. Blacks, Hispanics, and Asians, as well as those in other racial and ethnic groups (mostly American Indians in the Census), still represent a relatively small portion of college-educated workers, but their representation has grown over time.

Given these substantial demographic changes, how might we expect wage inequality to have changed over this same period? One possibility is that wage gaps between advantaged and disadvantaged groups have *widened* over time. This may have occurred because, as other studies have shown, contemporary inequality trends have been dominated by the growing gap between the top and middle of the wage distribution, with incomes at the top having taken off (Autor 2014; Keister 2014). To the extent that advantaged groups (e.g., men, whites) are concentrated at the top of the wage distribution, wage gaps between advantaged groups and all others may have widened over time. An alternative, more social-psychological mechanism is that because advantaged groups are becoming rarer in the population of college-educated workers, employers may place more of a premium on male-ness, white-ness, and membership in other advantaged groups as time has passed (although this mechanism is not possible to test with Census data). A second possibility is that wage gaps between advantaged and disadvantaged groups have *shrunk* over time. As women and racial minorities have earned more college degrees, and Americans' attitudes toward these groups have liberalized over time (notwithstanding a vocal opposition), it follows that college graduates in these ascriptive categories would be able to attain wages that are similar to those in advantaged groups.

A third possibility raised by recent research is that gaps have simultaneously widened *and* shrunk, but at different locations of the wage distribution. Given that such a substantial proportion of inequality growth has occurred among high wage-earners who are largely concentrated in the college-educated workforce, it stands to reason that multiple wage gaps among college workers could emerge during an era of simultaneous college expansion and growth in higher education returns. In other inequality literatures, scholars show that the growth of inequality over the past four decades has led to different *distributional properties* of inequality (Alderson, Beckfield, and Nielsen 2005; Western et al. 2008; Western and Rosenfeld 2011; VanHeuvelen 2018b, 2018c), a methodological approach that suggests the examination of simple conditional mean wage gaps—frequently used in studies of ascriptive inequalities—may be of declining use in explanations for inequality. Lin (2015), for example, shows that premiums in the finance and securities industries have become increasingly concentrated among top-end pay, while Fortin et al. (2009) show that union membership is associated with higher *and* lower wages across the wage distribution. In this article, we adjudicate between these perspectives—i.e., whether wage gaps among college-educated workers have widened, shrunk, or both—and the extent to which these trends apply to a wide range of ascriptive categories.[3]

Accounting for Majors and Advanced Degrees

After documenting trends in ascriptive wage gaps from the mid-20th century to the present era corresponding with the substantial changes to the college-educated workforce, we consider how major choice in recent years contributes to wage inequality among college workers. We also consider how wage gaps on account of major choice compare to, and help explain, those on account of gender and race/ethnicity. Research consistently shows that college students in different ascriptive groups tend to major in different fields. A large body of research focuses on gender as a predictor of field of study because many fields are broadly understood as either male-dominated (e.g., STEM fields – science, technology, engineering, mathematics) or female-dominated (e.g., education, nursing, the humanities; Charles and Bradley 2009; England and Li 2006; Jacobs 1996). Although gender is the most obvious basis on which majors are stratified, studies have also shown that students in different racial and ethnic groups are concentrated in different fields of study. Asian students, for example, are over-represented in engineering and computer science, while white students are over-represented in business (Dickson 2010).

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[3] Another possibility is that wage gaps between advantaged and disadvantaged groups have remained uniformly stable over time, although we believe this is unlikely, given the substantial demographic changes to the population of college-educated workers and the broad range of ascriptive categories in the Census data.

Fields of study have broad consequences for inequality because they are associated with vastly different wages among college-educated workers.[4] Scholars have noted that part of these disparities may be attributable to the sex-typing of majors and their associated occupations (Levanon, England, and Allison 2009). But regardless of the reason for these inequalities, research indicates that the wage gaps between college graduates in different fields of study are sometimes larger than that between high school and college graduates. Those with bachelor's degrees in STEM fields, business, and health are generally on the upper end of the wage distribution, while those with degrees in the humanities, education, and (to a lesser extent) the social sciences are on the lower end (Kim et al. 2015).

Given the large inequalities between college graduates in different fields of study, this raises the question of how wage inequalities on account of major choice compare to those on account of ascriptive characteristics—in other words, whether major choices can close wage gaps associated with gender and race/ethnicity. Major choice is often framed as an agentic form of inequality because most students have some amount of choice in what they will study in college. In fact, a common implication in the literature on major choice is that wage gaps between women and men, and between workers in different racial/ethnic groups, could be largely closed if those in disadvantaged groups were to choose majors that are high-paying at the median. In studies of gender, for example, some scholars have used methods such as the dissimilarity index (DI), which estimates the proportion of women (men) who would have to change majors in order to be distributed similarly to men (women; see e.g., England and Li 2006;

[4] Although our analyses focus on the relationship between majors and earnings, we acknowledge that majors vary in the extent to which they translate to specific jobs (Roksa and Levey 2010), and college graduates who majored in the same fields often work in diverse industries and have diverse job titles and duties.

Jacobs 1995; Turner and Bowen 1999)—one potential implication being that women would benefit if they were to change their majors accordingly. But for all the focus on distributional differences between ascriptive groups, no studies (to our knowledge) have assessed whether major choices are able to overcome inequalities on account of gender and race/ethnicity. Thus, a key objective of this article is to determine whether major choice can alleviate the more structural forms of inequality we observe on account of gender and race/ethnicity, as described further below.

DATA & METHODS

We use 17 waves of longform Census and American Community Survey (ACS) microdata (Ruggles et al. 2017). Census data are from years 1960, 1970, 1980, 1990, and 2000, while ACS data are from individual years between 2005 and 2017. Census waves comprise either a 5 percent sample (1960, 1980, 1990, 2000) or 1 percent sample (1970) of the U.S. population, while yearly waves of the ACS correspond to approximately 1 percent samples of the U.S. population. In the main analyses, we restrict samples to respondents who work 400 or more hours annually, are between the ages of 25 and 64, and who have completed four years of college or more.[5] We exclude respondents who are self-employed, those who report no income, those who are out of the labor force, and those who live in group quarters.

Census and ACS data are ideal for our analyses. The Census provides reasonably detailed categories of race and ethnicity over a long period of time, while ACS data from 2009 onward provide comprehensive information about college degrees. Further, the large and nationally-

[5] Census codes of educational attainment vary across years. In the 1960 Census, for example, respondents were asked to report years of college completed, while in the ACS, respondents were asked to report degrees completed. For consistency, our sample includes respondents who indicated they had completed either four years of college or a bachelor's degree.

representative samples allow for the measurement of group differences in wages even *within* college major categories. This is a strength compared to other data sources, such as the Survey of Income and Program Participation (SIPP), the National Longitudinal Survey of Youth (NLSY), or datasets from the National Center for Education Statistics (NCES), such as Baccalaureate and Beyond (B&B), which have relatively small sample sizes compared to the Census and ACS. Our analyses include 3.51 million college-educated wage earners across the 2009-2017 ACS waves, which provides sufficient sample sizes for the upwards of 1,224 gender-by-race/ethnicity-by-major categories, which we use in the most fine-grained analyses as described below.

Variables

Our main outcome is logged wage. We construct this measure as the respondent's total pre-tax wage and salary income (or all wages, salaries, commissions, cash bonuses, tips, and other monetary income received from an employer), divided by annual hours worked. Wages are adjusted to 2009 dollars using the personal consumption expenditure index (Bureau of Economic Analysis 2018), bottom-coded as half the federal minimum wage (Goldin and Margo 1992), and top-coded as 1.5 times the top-code.[6]

When comparing across Census and ACS microdata, we use six race/ethnicity categories: (1) white, (2) black, (3) Asian, (4) white Hispanic,[7] (5) nonwhite Hispanic, and (6) other.[8] In analyses using ACS data, we have more detailed information about those in the Asian category, thus yielding the following 12 categories: (1) white, (2) black, (3) Chinese, (4) Japanese, (5)

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[6] In years 2000 and onward, top-codes are state-specific. To allow for comparability across years, we follow the top-coding strategy of Acemoglu and Autor (2011) by providing a uniform year-specific top-code value.

[7] Hispanic categories are imputed in the 1960 and 1970 waves by the IPUMS. Imputation is based on Hispanic birthplace, parental birthplace, grandparental birthplace, Spanish surname, and/or family relationship to a person with one of these characteristics.

[8] In most Census waves, the o*ther* category is comprised primarily of American Indians.

Filipino, (6) Asian Indian, (7) Korean, (8) Vietnamese, (9) other Asian, (10) white Hispanic, (11) nonwhite Hispanic, and (12) other. We also examine wage differences by gender (men or women). Descriptive statistics for these main variables of interest from the Census and ACS are included in Table 1.

(Table 1 about here)

We measure college major using three separate coding schemes that have been used in prior research. In most of the main analyses, we follow Altonji and colleagues (2016) and code majors into 51 categories developed by the U.S. Department of Education. In other analyses, to ensure robustness of the 51-category scheme, we use either the seven broad categories proposed by Kim and colleagues (2015)—these are business, STEM, health, social sciences, education, liberal arts, and other (see also Quadlin and Cohen 2018)—or the 38 major categories used in the U.S. Census. These three coding schemes, and the distributions of respondents across majors for each coding scheme, are shown in Table 2.[9]

(Table 2 about here)

In regression analyses, we control for ten sets of variables.[10] These include: whether the respondent has an advanced degree; a quartic function of age; 19 industry categories (Western and Rosenfeld 2011);[11] public employment status; whether the respondent lives in a metropolitan area; state fixed effects; year fixed effects (when years are pooled); eight family status categories, which we constructed by interacting four marital status categories (married,

[9] In sensitivity analyses, we examined results with interactions between college major and whether the respondent held an advanced degree. Results are substantively similar to those presented below.
[10] Descriptive statistics for control variables are available from the authors upon request.
[11] Specifically, we use Western and Rosenfeld's (2011) 18 industry codes, plus public administration.

divorced/separated, widowed, never married/single) with whether the respondent has their own children present in the household; whether the respondent has their own young children (aged 5 or under) present in the household; and the number of children present in the household.[12]

Methods

We use three main methodological approaches to examine results. The first approach assesses general trends in wage gaps among college graduates. Specifically, we use linear regression with robust standard errors to predict mean adjusted logged wage gaps. In initial analyses, which use the full Census and ACS microdata samples, we measure predicted adjusted wage differences across gender and race/ethnicity, net of controls. In later analyses, we examine wages in relation to both college major and respondents' ascriptive characteristics. In these analyses, we estimate regression models separately by college major, and compute the adjusted average wage difference across the 24 gender-by-race/ethnicity categories.

The second and third approaches examine wage gaps among college graduates at particular points in the wage distribution. We begin by using unconditional quantile regression models, estimated using recentered influence function (RIF) regression models developed by Firpo and colleagues (2009, 2011, 2018). These models are based on the influence function (IF), IF($Y;v,F_y$), a well-established statistical tool from robust statistics (Hampel 2005). Y is the outcome variable under consideration. v refers to some statistical functional, $v(F_y)$, which in our case is a particular quantile in the distribution of wages, and F_y refers to the cumulative distribution function of Y. Simply put, an influence function quantifies how a statistical functional changes in response to an infinitesimal change in the data. Influence functions are

[12] In sensitivity analyses, we assessed whether results varied by parental status. Generally, we found that parental status did not substantively affect results; select results are described in footnotes below.

centered at zero. When the statistic $v(F_y)$ is added back to the influence function, this results in the recentered influence function, RIF. Formally, this is written as:

$$RIF(y; v, F_y) = v(F_y) + IF(y; v, F_y)$$

For a particular quantile, the conditional expectation of the *RIF(Y;v,F_y)* can be modeled as a function of a set of variables, *E[RIF(Y;v,F_y)|X]*. In our case, the distributional statistic of interest is a quantile in the wage distribution, but alternative statistics could include the Gini coefficient, variance, log wage gaps across quantiles, and, in a case that reduces exactly to OLS regression, the mean. Formally, this is written as:

$$E\left(RIF(Y; v, F_y) \middle| X\right) = X\beta$$

Where the coefficient β represents the marginal effect of X on the quantile of interest. Substantively, RIF regressions approximate wage differences associated with marginal changes in the covariates, such as the wage difference between men and women, at particular quantiles of interest, such as the median, 90th wage percentile, 10th wage percentile, etc., net of other observed factors. Standard errors are bootstrapped to account for estimate uncertainty.[13]

In addition to these RIF regressions that assess how groups differ in wage attainment across the unconditional distribution of wages, we are also interested in examining the relative importance of group composition and major choice for the wage inequalities observed among college-educated workers. One method frequently used by social scientists to detect the relative importance of compositional gaps across groups in relation to unequal returns to compositions is the Oaxaca-Blinder (OB) decomposition. Usually used as a tool to assess the sources of mean differences between two groups, the OB decomposition uses separate linear regression models in

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[13] Readers interested in the technical details and mathematical derivations of RIF regressions can refer to writings by Firpo and colleagues (2009, 2011, 2018).

two groups to parse mean wage gaps into two portions: [1] *composition effects*, or differences in the outcome attributable to the uneven distribution of observed characteristics across groups, and [2] *wage effects*, or differences in the coefficients across groups associated with observed characteristics, as well as differences in the intercepts. Formally, the OB decomposition is written as:

$$\bar{Y}_a - \bar{Y}_b = \sum(\bar{X}_a - \bar{X}_b)\beta_a + \left[\sum \bar{X}_b(\beta_a - \beta_b) + (\alpha_a - \alpha_b)\right]$$

The first portion of this decomposition refers to the composition effect, and the bracketed second portion refers to the wage effect.

Firpo and colleagues (2018) demonstrate that the OB decomposition of mean wage differences across groups is simply a particular instance of a more general decomposition of any distributional statistic (see also Lin 2015). Thus, RIF regressions estimated separately across two groups, such as men and women at some particular quantile, v_m and v_f, can be decomposed similarly to the way mean gaps can be decomposed.[14] The logic is extended to view $\bar{Y}_a - \bar{Y}_b$, shown above, as a general difference in wages across two groups measured in terms of some distributional statistic, of which the mean is a special case. We thus apply OB decompositions across the entire wage distribution of college workers to see where, and at what magnitude, differences in college major composition and returns affect wage gaps between groups.

RESULTS

To What Extent are College Graduates' Wages Unequal?

We begin by assessing the extent to which college graduates' wages are unequal in the U.S. One way to gauge this is to compare the levels of inequality experienced by college-

[14] Firpo and colleagues (2018) recommend that RIF decompositions be estimated on samples reweighted with the logic of Dinardo, Lemiuex, and Fortin (1996). We use this reweighting strategy in results presented below.

educated workers to that of non-college-educated workers. The top panel of Figure 2 charts these two measures of wage inequality over time, with an additional line representing the total inequality trend. This figure clearly shows that bachelor's degree-holders account for most of the wage inequality among U.S. workers as a whole—a trend that has only accelerated in recent years. Between 1960 and 1990, wage inequality trends among the college-educated were largely stable. From 1990 onward, however, wage inequality has increased steadily for college graduates, from approximately .375 to over .45—and approaching .50 in the wake of the Great Recession. Inequality among those without bachelor's degrees has also grown over this period, but it remains considerably lower than that for college graduates. In addition, the gap in inequality between education levels has increased substantially since 1990, and has ballooned since 2010, implying that the rate of inequality growth has increased for college-educated workers as compared to non-college-educated workers.

(Figure 2 about here)

The bottom panel of Figure 2 illustrates a counterfactual trend of inequality change. Here we show: the total change in wage inequality relative to 1960 ("observed inequality"); the predicted inequality change had the inequality between those with and without a college degree remained at 1960 levels ("college premium held at 1960 value"); the predicted inequality change had the inequality among those with a college degree remained at 1960 levels ("within-college inequality held at 1960 values"); and the predicted inequality change had the inequality among those with and without a college degree remained at 1960 levels ("within-education inequality held at 1960 values"). Although scholars in recent years have paid substantial attention to the returns associated with higher education, these results show that growth in inequality among the college-educated has been at least as consequential for total inequality trends as the wage gap between college and non-college workers. Especially since the Great Recession, within-college inequality has emerged as more important than between-college inequality. To summarize, then, wage inequality among college degree holders is large, has grown larger over time, and now contributes more to total inequality trends than the college premium.

(Figure 3 about here)

Another way to gauge inequality among college-educated workers is to assess how wages have changed at various points in the wage distribution. We do this in Figure 3 by showing wage changes across the wage distribution for three levels of educational attainment: high school or less (left panel), some college (middle panel), and college or more (right panel). Rainbow lines are used to show the percent change in the wage value at a particular income quantile, from the 5th percentile (deep purple) to the 95th percentile (red) over time. These panels show that college inequality is unique for several reasons, most notably the fact that wage changes line up almost perfectly with respect to income quantiles in this group. Among college-educated workers, wage changes have clearly taken off for those with the very highest incomes and slowed for those with lower incomes. This has not necessarily been the case for those with lower levels of educational attainment—especially those with a high school diploma or less, where wage gains have been greatest for those in the 5^{th} percentile.

Based on these results, we surmise that focusing on income quantiles is important for assessing inequality change among college-educated workers. Further, the biggest drivers of college inequality—those in the 90^{th} percentile and above, or the red and orange lines in Figure 3—appear to be an important locus of advantage that is key to understanding stratification in this group. We use these insights to inform subsequent analyses by focusing on group-specific wages not only in the aggregate, but also across the wage distribution.

Whose Wages are Unequal among College Graduates?

Among the college-educated, which ascriptive groups are likely (and unlikely) to experience wage inequality? In this section, we assess wage gaps over time by gender and race/ethnicity to determine the extent to which demographic groups account for inequality. Additionally, in light of the fact that central tendencies reveal only part of the social dynamics of wage attainment, as well as our observation that wage quantiles capture an important dimension of wage changes among the college-educated, we examine these groups at several points in the wage distribution.

Table 3 shows gender wage gaps estimated separately by race/ethnicity groups. We show change over time by presenting results from 1960 and pooled ACS waves 2011-2015.[15] The "average" columns show the group-specific gender wage gaps at the specified time point, generated using OLS models. For the columns labeled "pctl," we replicated the OLS models using re-centered influence function (RIF) regression models to estimate gender wage gaps at the 10^{th}, 50^{th}, 90^{th}, and 95^{th} wage percentiles. The estimates in Table 3 are adjusted for the control variables outlined in the methods section; unadjusted wage gaps, without controls, are shown in the online supplement.

(Table 3 about here)

We begin by looking at the average gender wage gaps in 1960 versus 2011-15. Overall, the results reveal the emergence of a broadly shared gender wage gap over time. In 1960, few groups experienced a gender wage gap net of controls. The exceptions are white workers—where female wages are approximately 17% lower than equivalent male wages—and other workers

[15] We also visualized changes across all Census waves and across birth cohorts as robustness checks, and found that these reiterated the patterns shown in the main text. We restrict attention to these two time points to streamline the presentation of results.

(primarily comprised of American Indians and Alaskan natives)—where female wages are approximately 15% lower than male wages. By 2011-15, universal and robust gender wage gaps emerged across all groups of college-educated workers. Gender wage gaps among white workers grew to approximately 20%, while gender gap among other groups ranged from 8% (Black) to 15% (other and non-white Hispanic). Thus, as women joined the ranks of the college-educated workforce, a uniform gender wage gap emerged across all racial/ethnic groups.[16]

The RIF regression results show that much of the emerging uniform gender gap has been concentrated at the middle and top of the wage distribution. In 1960, 8 out of 18 comparisons at the 50th, 90th, and 95th percentiles indicated no significant gender gap in wages (and one comparison, Black workers at the 90th percentile, shows a significant wage advantage for women). Notably, half the comparisons at the 95th percentile were not significant in 1960. By 2011-15, however, a significant gender difference is detected across all groups at the 50th percentile and above. We also observe that the wage gap has remained consistent toward the bottom of the distribution, but has grown in the middle, and especially at the top. Between 1960 and 2011-15, the wage gap held at 11% at the 10th percentile; grew from 16% to 19% at the median; grew from 18% to 27% at the 90th percentile; and grew most substantially from 21% to 41% at the 95th percentile. Thus, although a broadly shared gender wage gap among college-educated workers has emerged over time, this pattern has become particularly pronounced at the top of the wage distribution.

[16] In supplementary analyses, we replicated these average gender wage gaps among workers with a high school degree or less. In contrast to the patterns we observe among college-educated workers, this analyses shows a *decline* in adjusted female wage gaps for nearly all race/ethnicity groups over time. We conclude that the gender wage gap has shifted over time to the college-educated segment of the workforce.

Table 4 presents predicted differences in wages across race/ethnicity groups, by gender. Looking at the averages for women, we see that in general, a broadly shared race/ethnicity wage gap has emerged over time. In 1960, only Black women had lower wages than white women—but by 2011-15, workers in other racial/ethnic groups, white Hispanics, and non-white Hispanics (in addition to Blacks) experienced a wage gap as well. The notable exception is Asian women, who had wages comparable to white women in 1960, but had higher wages than white women by 2011-15. In contrast, wage gaps for men were substantially larger than that for women in 1960, and (with the exception of those in other racial/ethnic groups) these gaps shrunk by varying degrees over time. The wage gap shrunk from -.27 to -.21 for Blacks, from -.22 to -.17 for white Hispanics, from -.18 to -.15 for non-white Hispanics, and reached parity from -.08 for Asian workers.[17] In summary, while women's wages often grew more unequal over this period, men's wages frequently grew closer to those of white workers.

(Table 4 about here)

Next, we assess the RIF regression results for women and men. The results for women suggest uneven growth in inequality over time, partly as a function of small cell sizes for women college graduates in 1960 (for example, the .36 wage advantage for white Hispanic women in 1960 is not statistically significant on account of small cell sizes). Yet, most of the biggest changes over time have occurred at the 90th and 95th wage percentiles. For Asian women—the only group with an advantage over white women—the biggest changes have likewise come at the top of the wage distribution. The wage gap for Asian women relative to whites grew 13% at the 90th percentile, and 16% at the 95th percentile, giving top-earning Asian women a sizeable wage

[17] Results are similar when we replicate these average race/ethnicity wage gaps using workers with a high school degree or less.

advantage by 2011-15. For men, we see some narrowing of wage gaps at the bottom and middle of the distribution, coupled with widening of wage gaps at the top. Asian men have reached parity with white men over time, and even have a wage advantage at the median. Overall, then, although women's and men's wages have not followed parallel trajectories in terms of inequality, we see a consistent pattern of white and Asian high-wage earners distancing themselves from other groups. Most of the shrinkage in inequality we see among men is attributable to low and median wage-earners.

To provide a substantive sense of these changes, Figures 4 and 5 present changes in gender and race/ethnicity wage gaps over time at the 10^{th}, 50^{th}, 90^{th}, and 95^{th} percentiles. Here we focus on the four largest race groups in the data (white, black, non-white Hispanic, and Asian) for ease of presentation. Figure 4 visualizes gender wage gaps, and clearly shows the emergence of a consistent wage gap over time, spearheaded by high wage-earners at the 90^{th} and 95^{th} percentiles. Although the magnitude of the high-wage gap is much larger for white workers than for Black, non-white Hispanic, or Asian workers, the wage gap among high wage-earners is consistently higher than the mean gender difference for all groups (indicated by the dotted line). Additionally, for all groups, gender wage gaps are closest to zero for those in the 10^{th} percentile of wages.

(Figure 4 about here)

Figure 5 shows these same changes over time, but compares Black, non-white Hispanic, and Asian workers to white workers (separately for women and men). For Black and non-white Hispanic workers, we see the emergence of a consistent wage gap over time, with results driven especially by high-wage men. In contrast, wages for Asian workers have converged with or even exceeded those of white workers, especially among women.

(Figure 5 about here)

In summary, the patterning of these wage gaps suggests that advantage has become increasingly concentrated among men, white workers, and Asian workers at the upper end of the wage distribution. Although college access has democratized since the 1960s, we find that economic advantage at the top (with some notable exceptions) is tightly linked with the most privileged ascriptive groups.

Can College Majors Close Ascriptive Wage Gaps among College Graduates?

To what extent can college major choice close gender and race/ethnicity wage gaps among college graduates? Perhaps the historical variation of wages among high-wage workers simply reflects greater selection of men, white workers, and Asian workers into high-paying majors, such as engineering and finance. Many scholars and members of the public have argued that group-based wage gaps could be closed, and individual returns to higher education could be improved, if students choose majors that are high-paying on average—in other words, that agentic sources of inequality, such as major choice, can overcome structural sources of inequality, such as gender and race/ethnicity. To assess whether this is the case, we first examine wage gaps within majors and across gender and race/ethnicity groups. This provides an initial description of how major choice and ascriptive characteristics contribute to college workers' wages. Then, we evaluate the extent to which major choice can alleviate the wage inequalities we observe among college graduates.

First, to provide a descriptive sense of the relationships between major choice, gender-race/ethnicity, and wages, we examine wage gaps within majors and across ascriptive groups. Specifically, we assess major-specific adjusted wage differences across 24 gender-by-race/ethnicity categories, as described in the methods section. Figure 6 shows these results across three panels, reflecting the three major coding schemes we used (see Table 2). Regardless of which coding scheme used, we find substantively large within-major adjusted wage differences across gender and race/ethnicity groups. When we use the seven-major coding scheme (left panel), within-major wage gaps range from about 0.30 to 0.55. When we use the 51-major coding scheme (right panel), these gaps range from about 0.28 to 0.95.

(Figure 6 about here)

Figure 6 makes one point in particular very clear: wage gaps within college majors are comparable in size, and sometimes even larger, than the maximum wage gap across college majors. The vertical lines in each panel show the maximum predicted wage difference for workers with bachelor's degrees in different majors. For example, in the right panel, the vertical line indicates that the wage difference between those who majored in philosophy/religion (the lowest-paying major) and chemical engineering (the highest-paying major) is approximately 0.57, or 77% ((1-$e^{0.57}$)*100). For nearly all majors in this panel, we observe a wage gap within majors that is at least two-thirds of the maximum wage difference between majors. For about one-third of these majors, the wage gap across gender-race/ethnicity is even *larger* than the maximum between-major wage difference. This pattern suggests that—at least at this initial stage—major choice, in many cases, is unable to overcome the power of ascriptive characteristics in shaping wage inequality.[18]

[18] We conducted a range of supplementary analyses to assess the potential causes of these gaps and well as the robustness of the results. We examined: (1) changes across ACS waves; (2) changes across birth cohorts; (3) results among those aged 21-35 with no children in the household, to remove the confounding effects of the motherhood penalty; (4) results with a simpler six-category measure of race/ethnicity; and (5) results using the 90-10 range of within-major wage differences instead of the maximum. In all cases, we found results that were similar to those shown here, suggesting that the within-major wage gaps we observe cannot be easily explained away by other frequently-cited trends in U.S. wage inequality.

Next, we synthesize the results by assessing systematically the relative contribution of college majors to wage gaps across groups. To do so, we apply the logic of Oaxaca-Blinder decompositions to unconditional quantile regression models. This method allows us to assess the relative impact of college major composition and wage effects at various points in the wage distribution. As we demonstrated earlier, ascriptive wage gaps are not uniform across the entirety of the wage distribution, and it stands to reason that college major selection would vary across the wage distribution as well.

Figures 7 and 8 present a selection of all possible decompositions. Figure 7 presents results for gender gaps, and Figure 8 presents results for racial/ethnic gaps. In both of these figures, the panels in the left column present the observed wage gap at particular quantiles (black line), the explained portion due to compositional differences (blue line), and the unexplained portion due to wage effects (red line). The middle panels show the relative contribution of college major composition effects to the total observed gap. The right panels show the relative contribution of college major wage effects to the total observed gap.

(Figure 7 about here)

Figure 7 generally shows that college major selection has little explanatory power over wage gaps between men and women. The left panels reiterate the point that for white, black, non-white Hispanic, and Asian workers, gender gaps are largest at the top of the wage distribution. In the middle panels, we see that college major composition effects fare poorly as an explanation for gender wage differences. For white and Asian workers, the relative contribution of major composition effects declines at higher wage levels, while compositional differences remain relatively stable at low magnitudes for Black and non-white Hispanic workers. The right panels show that positive college major wage effects tend to emerge in the upper half of the wage distribution. Put differently, at the upper end of the wage distribution, in cases where men and women major in the same fields of study, men have higher relative returns than women. Here, also, wage effects and composition effects are approximately equal in magnitude. In summary, these results show that even if college major selection could be equalized between men and women, substantial wage differences would remain. Even when men and women have bachelor's degrees in the same fields of study, and net of industry differences and a host of other family, social, and economic factors, men and women are paid unequal wages. This is especially the case at the top of the wage distribution, where gender gaps are the largest.

We draw similar conclusions from Figure 8, which shows results for racial/ethnic wage gaps relative to white workers. The largest wage gaps tend to be at the top of the wage distribution, and college major compositional effects tend to fare the worst at this location. The comparison between white and Asian men is an illustrative case. Asian men have selected into college majors that yield higher average returns, and in the top half of the wage distribution, Asian men tend to receive higher relative returns to majors compared to their white counterparts. Yet these forces are not sufficient to equalize the wage gap between white and Asian men, as there is still a large wage gap among high-wage earners (above the 95th percentile) that is driven by unexplained factors.[19]

(Figure 8 about here)

[19] At first glance, the results for white and Asian men seem to contradict our finding in Table 4 that high-wage Asian men fare relatively well compared to their white counterparts. The models in Table 4, however, do not include a control for college major—once majors are controlled for in Figure 8, we find that high-wage white men have a substantial advantage compared to Asian men. This makes intuitive sense, considering that Asian men are over-represented in high-paying majors.

Overall, these figures demonstrate the power of gender and race/ethnicity in predicting wages among college-educated workers. In an era of democratized college enrollments, but also rising inequality, wage differences across ascriptive groups have evolved in such a way that more privileged groups tend to experience more advantage at the upper end of the wage distribution. Especially for these high-wage earners, equalizing college majors across gender and race/ethnicity would fare poorly as a solution to inequality. Counterfactual scenarios in which men and women, or white workers and workers of color, are sorted with perfect equality across college majors show that most of the largest wage gaps would remain. These results, therefore, support the claim that potentially vulnerable workers cannot choose their way out of lower wages. Rather, gender and race/ethnicity are far more consequential as sources of wage inequality among college graduates.

DISCUSSION & CONCLUSION

Using 17 waves of Census and American Community Survey (ACS) microdata, this article assesses wage inequality among college-educated workers. We examine the extent to which college graduates' wages are unequal, how this trend has changed over time, how inequality varies at different points in the wage distribution, and how structural factors—such as gender and race/ethnicity—as well as agentic factors—such as major choice—contribute to inequality within this group. The findings from this study have several implications for research on inequality and higher education.

We find that bachelor's degree-holders account for most of the wage inequality among U.S. workers as a whole, and this trend has accelerated in recent years, particularly since the Great Recession. This descriptive finding is a key contribution in and of itself. Most research on returns to higher education focuses on the college premium, or the average wage differential between those who have a bachelor's degree versus those who do not. Although this is a straightforward way of quantifying economic returns, and one that justifiably casts higher education in a favorable light, this necessarily overlooks inequalities within the population of college-educated workers. Contrary to what many studies on the college premium have implied, we find that within-college inequality contributes as much to total inequality trends as the college premium. We posit, therefore, that scholars should pay more attention to sources of within-group inequality for college graduates going forward. Moreover, we find that within-college inequality is unique in the sense that those at the top of the wage distribution are responsible for large increases in inequality in recent years. Here we emphasize that the analyses are restricted to wage-earners, so this result is not simply a function of ultra-wealthy entrepreneurs taking off from the rest of the sample. Rather, we observe substantial inequality among traditional workers who are not self-employed.

We find multiple patterns of wage inequality across social groups over time, but two in particular that should be emphasized. First, comparisons of male-female wage inequality between 1960 and 2015 show the emergence of a broadly shared gender wage gap over time. In other words, as women joined the ranks of the college-educated workforce, gender wage gaps emerged across all racial and ethnic groups. This finding may be surprising, considering that in 1960 there were many race/ethnicity groups that did not exhibit a gender wage gap, and in the intervening period, many policies have been introduced with the intention of shrinking the gender wage gap in size. Results from RIF regressions suggest that gender wage gaps are particularly pronounced at the top of the wage distribution, so high-wage men workers appear to be driving this broadly shared gender wage gap. On a more social psychological level, however, these patterns are consistent with a growing preference for men workers as women have entered the college-educated workforce en masse. Social scientists have frequently shown that women face penalties in perceptions of their competence and ability. Although college-educated workers are broadly considered “skilled” in economic parlance, men and women may not be perceived as equally skilled, even if they have the same credentials.

Second, we find that wage inequality across race/ethnicity groups has been more varied over time, but the analyses generally point to a distancing of high-wage white and Asian workers from all other college graduates. This finding echoes prior research showing that incomes at the top of the wage distribution have taken off relative to those in the middle. Because many top earners are white and Asian college graduates, these groups account for much of the inequality we observe across racial/ethnic groups.

Major choice is one of the most frequently-cited sources of inequality among college-educated workers—and rightly so, considering the large wage gaps that are attributable to differences in fields of study. Prior research on major choice has implied that wage gaps could be closed between men and women, and between workers in different racial/ethnic groups, if those in disadvantaged groups were to choose high-paying majors. We sought to determine whether this is the case by assessing whether major choice can alleviate the wage gaps we observe on account of gender and race/ethnicity. The results demonstrate that major choice fares poorly as a solution to inequality among college workers. Even if major choice could be equalized across ascriptive groups, substantial wage differences would remain, especially at the top of the wage distribution.

In light of these findings, we contend that wage inequality among college-educated workers is primarily explained by structural factors, and cannot be closed through agency as some have implied. Many members of the public and even scholars have argued that college students have some degree of agency in determining their eventual wages, as they are free to choose a field of study that is associated with high wages at the median. Any wage gaps on account of major choice, then, could be rectified if students made different decisions about what to study—if they had only majored in engineering or finance, for example, rather than English or art history. To the contrary, these findings suggest that regardless of the majors students choose, their eventual wages are more strongly tied to their gender and race/ethnicity, which are more or less out of their control. Although major choice has often been touted as a reliable predictor of economic returns, we show that dynamics of group advantage and disadvantage are responsible for even larger variations in wages. Put differently, we find that potentially vulnerable workers cannot choose their way out of lower wages.

Although the Census and ACS data provide strong evidence of the scale of within-group inequality for college graduates, as well as some potential mechanisms, the data are not equipped to answer every question about why these patterns emerge. For example, the data do not contain information about the types of institutions respondents attended. Studies have shown that students in disadvantaged groups tend to attend less prestigious institutions, such as for-profit and open-access colleges, and these institutions, in turn, are associated with relatively poor labor market outcomes (Deming et al. 2016; Goldrick-Rab 2006). Thus, differences in institutional characteristics may account for some of the patterns shown here (although certainly not all, given the large and persistent effects of social status we observe, and the small proportions of students who attend elite colleges). Respondents' social class origins also are not included in the data, which have been shown to be tightly linked with economic standing in adulthood (see e.g., Sewell, Haller, and Portes 1969). Additionally, the data do not allow us to test some of the more social-psychological mechanisms that could help explain these patterns. Future research can assess, for example, the premiums employers attach to male-ness and white-ness given their lesser representation among college workers over time. A full investigation into within-group inequality will involve a combination of demographic and social-psychological inquiries.

Over the past 60 years, the college-educated workforce has experienced a great deal of expansion, diversity, and choice. This study shows that in the midst of its expansion, inequality among bachelor's degree-holders has been driven by diversity—or the structural dynamics of gender and race/ethnicity—and cannot be closed through choice—or the more agentic dynamics of fields of study. In the future, scholars can incorporate additional data and methods to investigate varying returns to higher education that go beyond the college premium.

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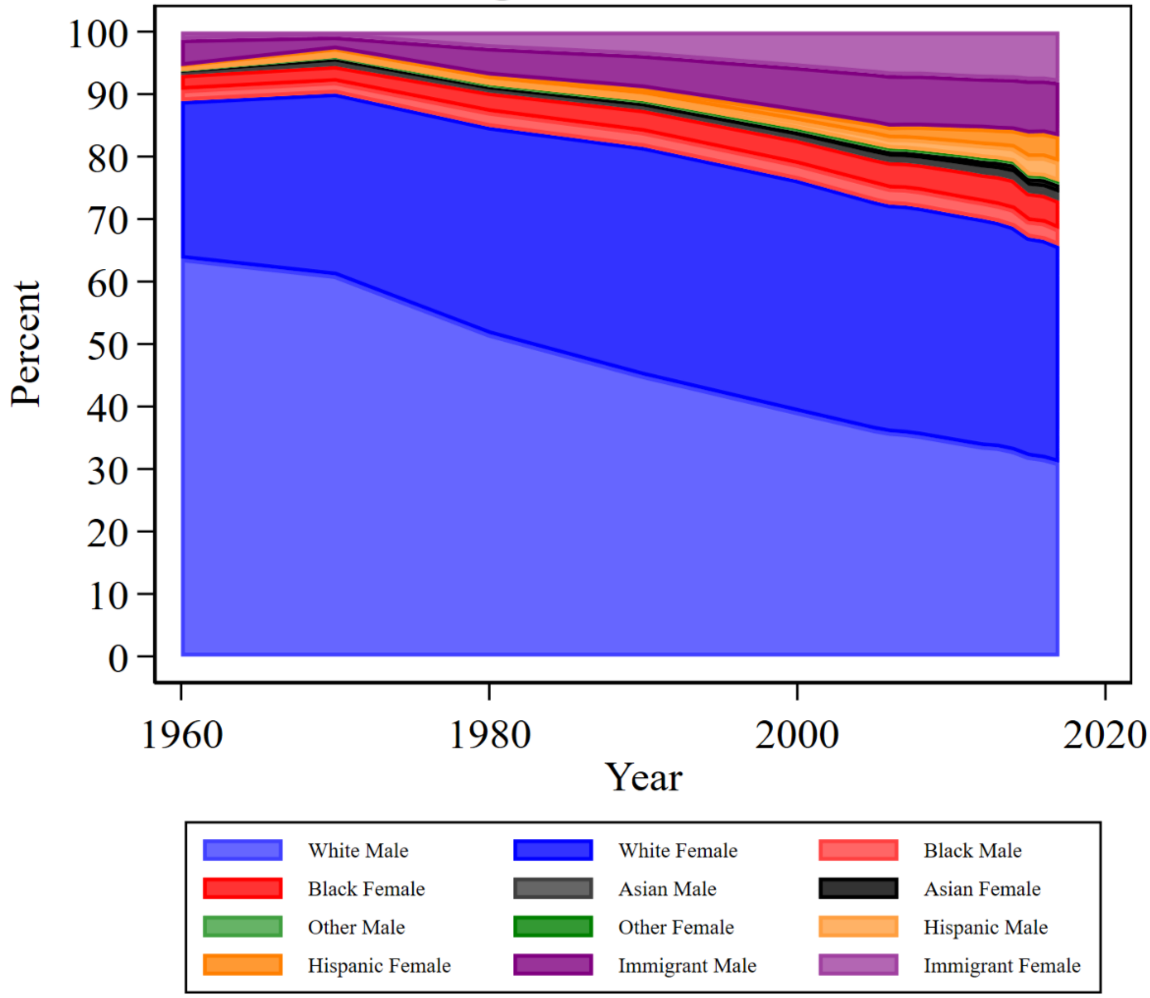
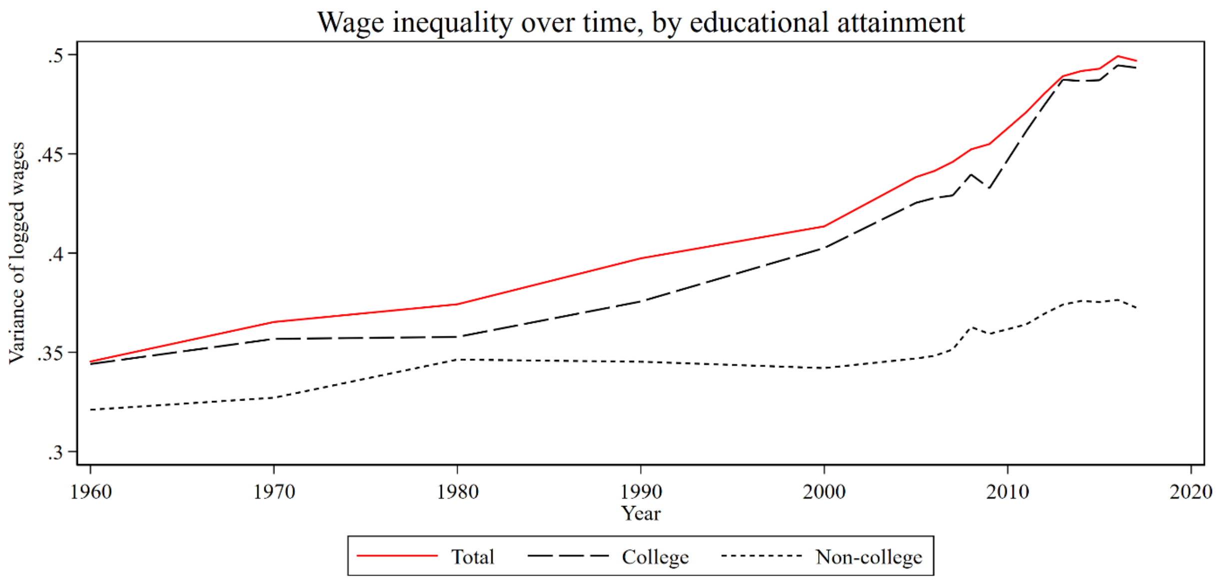
Figure 1: Demographic Composition of College-Educated Workers, 1960-2017



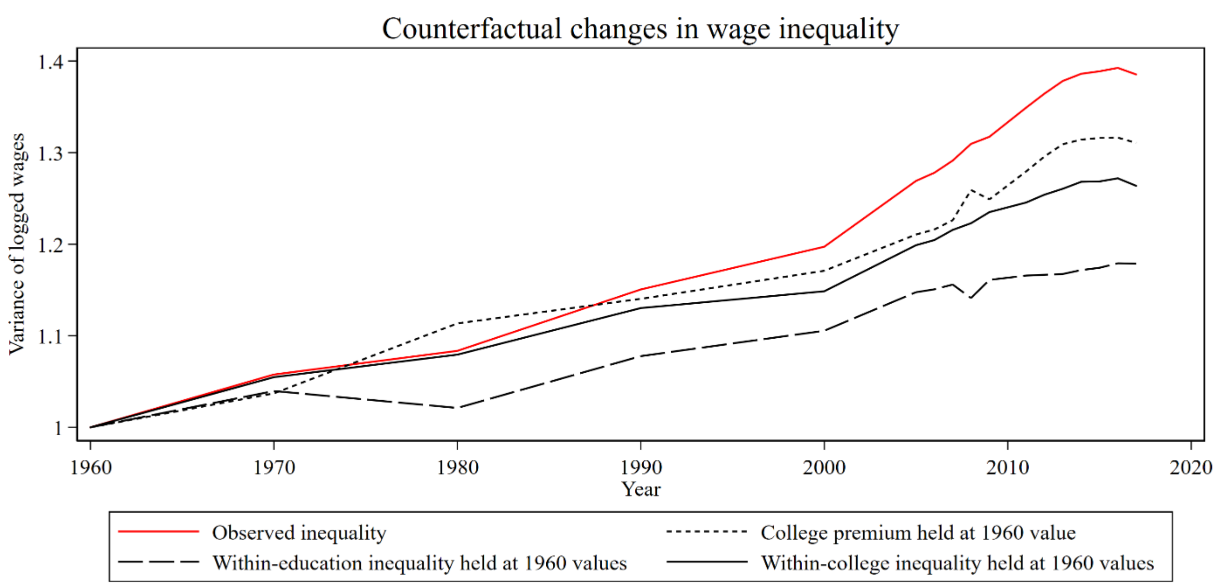
Source: Authors' calculations using Census and American Community Survey data.

Figure 2: Wage Inequality over Time, by Educational Attainment (Panel A); Counterfactual Changes in Wage Inequality (Panel B)

(A)

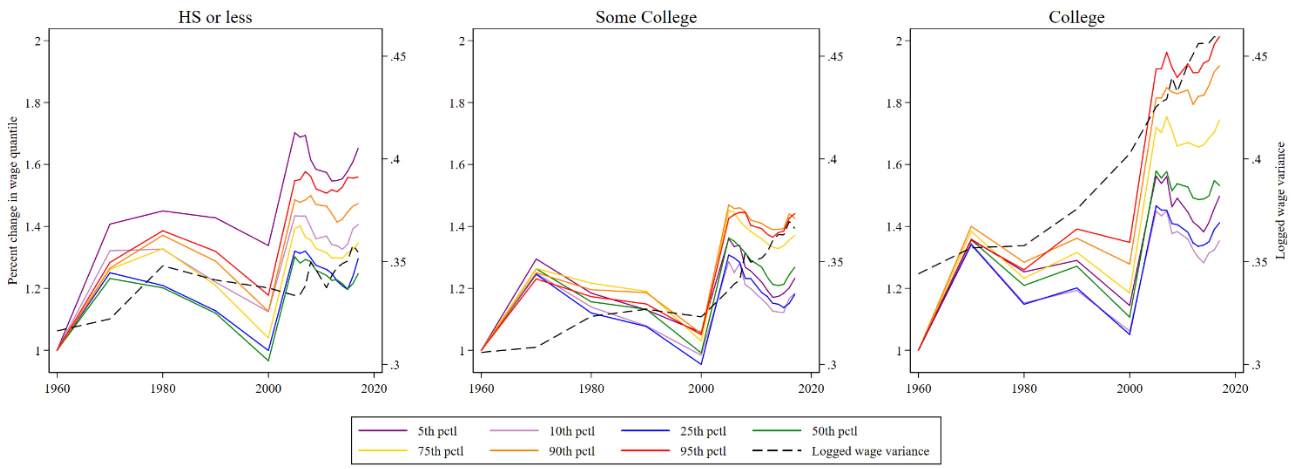


(B)



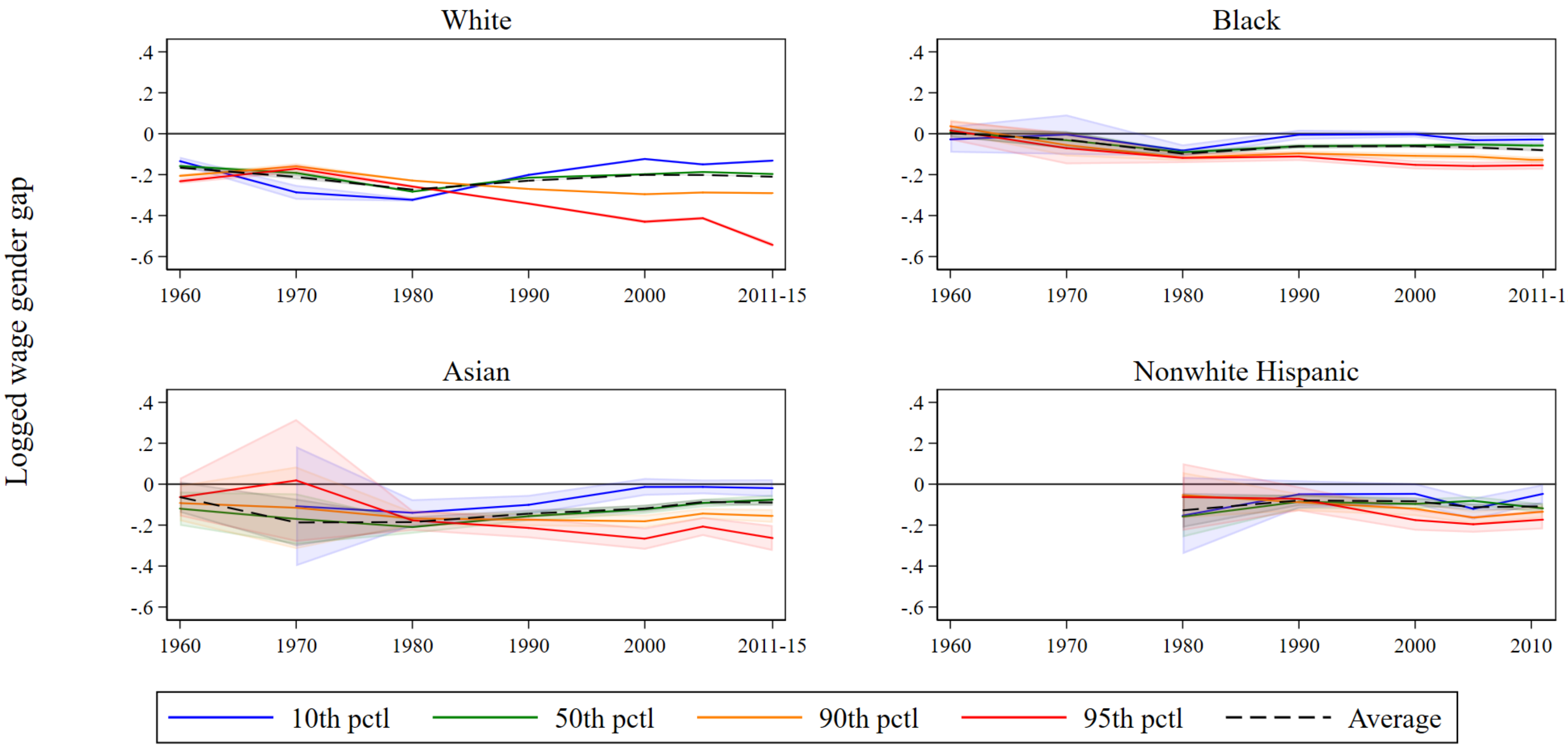
Source: Authors' calculations using Census and ACS data.
Notes: Data collected from samples of 25-64 year old non-self-employed workers with at least 400 annual hours worked and a college degree / four years of college.

Figure 3: Wage Inequality over Time, by Educational Attainment and Wage Quantile



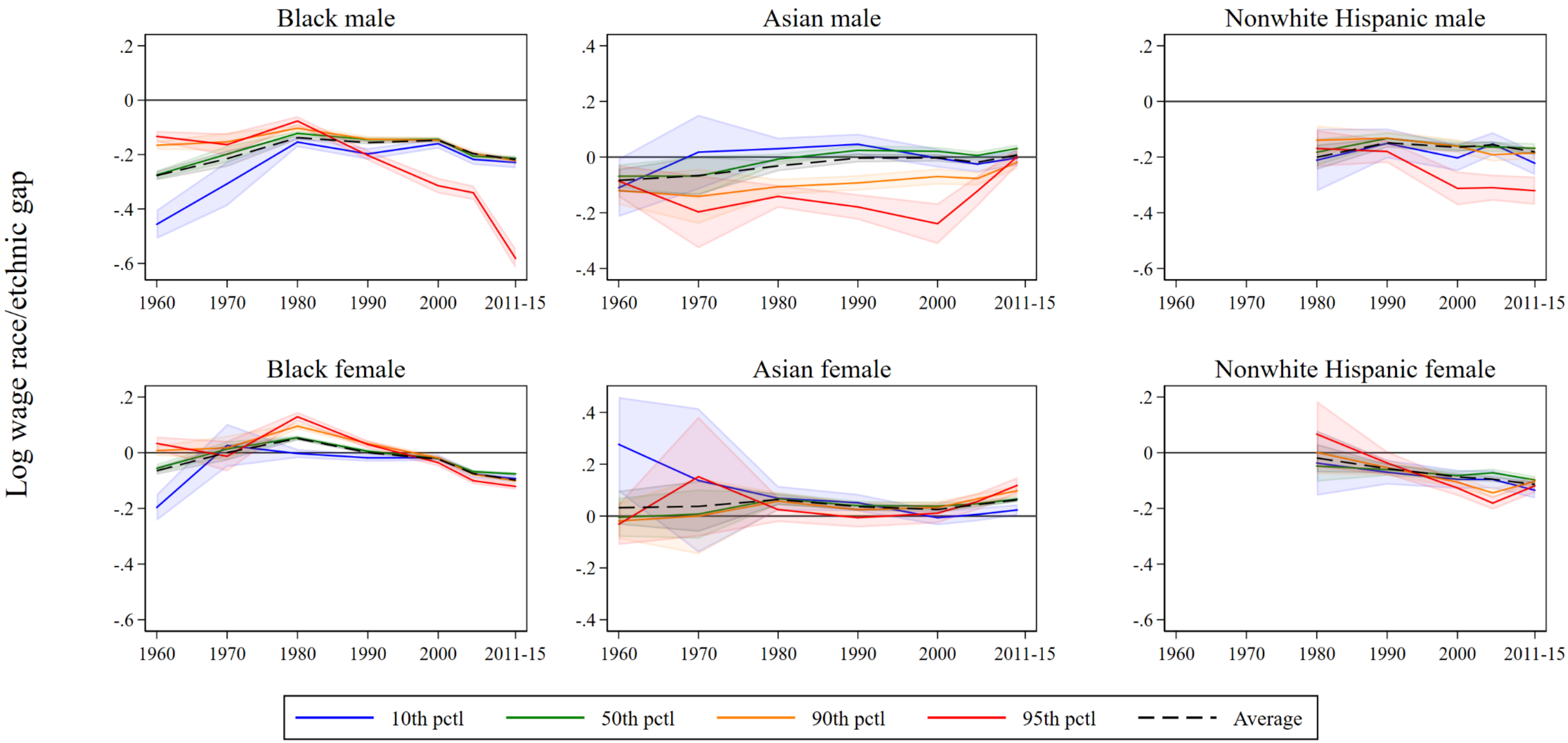
Source: Authors' calculations using Census and ACS data.
Notes: Data collected from samples of 25-64 year old non-self employed workers with at least 400 annual hours worked and a college degree / four years of college.

Figure 4: RIF Regression Change over Time – Gender



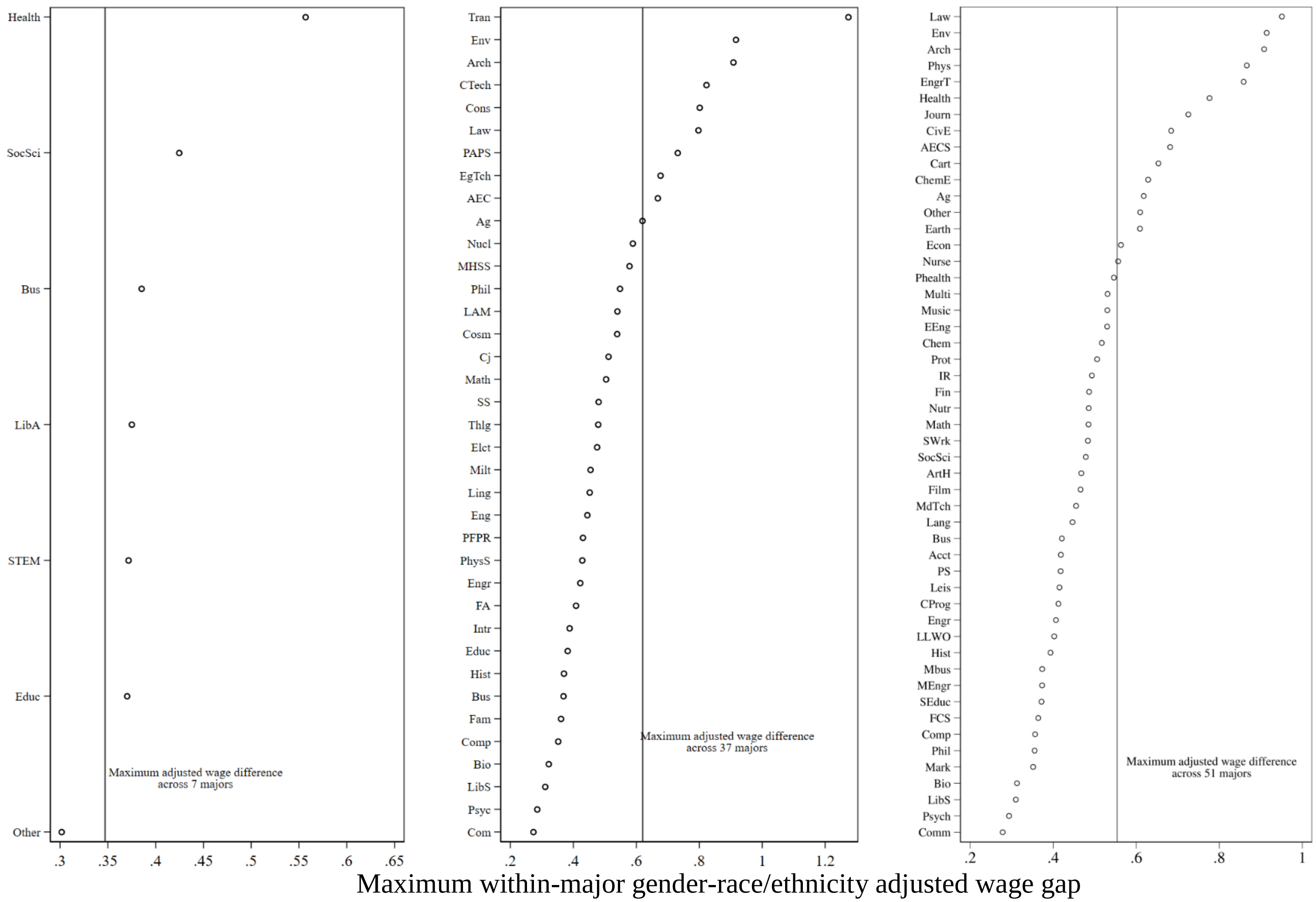
Source: Census 1960-2000, ACS 2005-2015.
Notes: Shaded areas = 95% confidence intervals. Some predictions have been omitted from 1960 and 1970 due to small sample sizes/large confidence intervals.

Figure 5: RIF Regression Change over Time – Race/Ethnicity



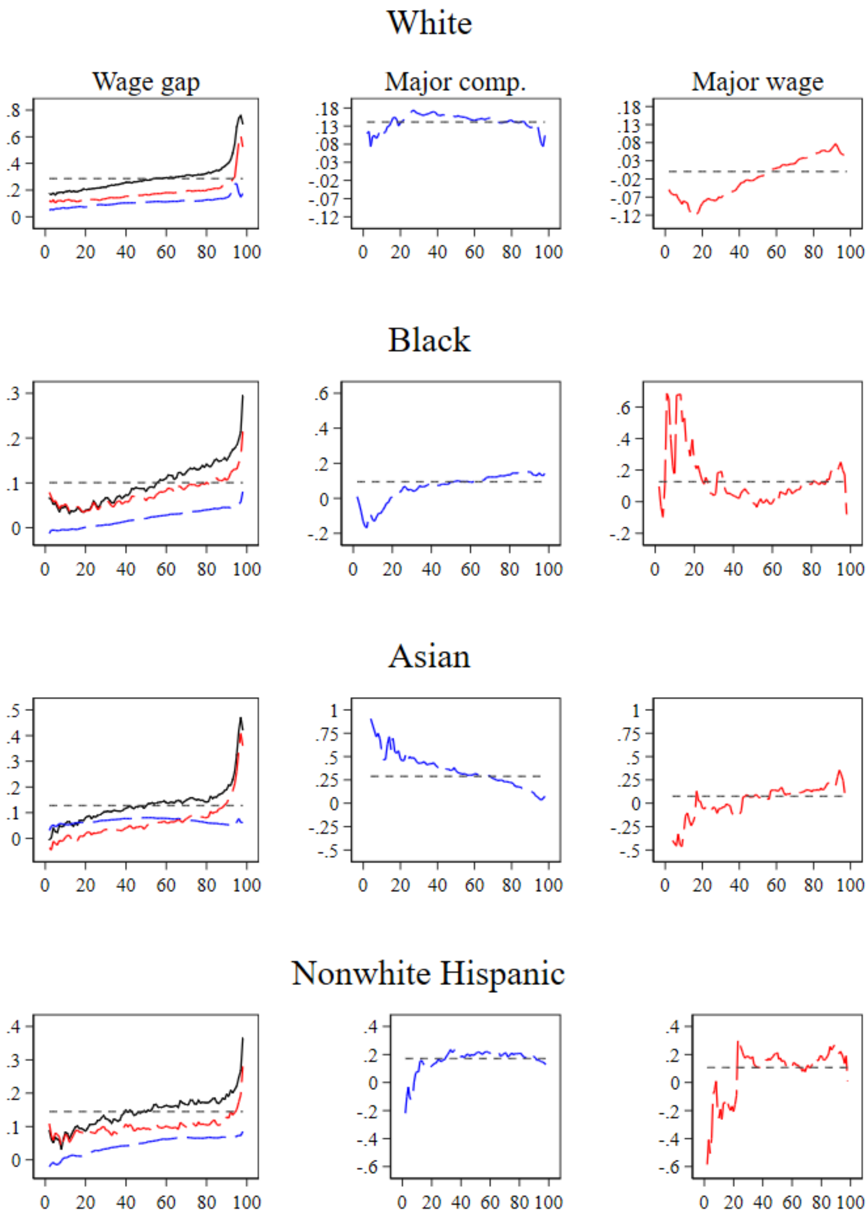
Source: Census 1960-2000, ACS 2005-2015.
Notes: Shaded areas = 95% confidence intervals. Some predictions have been omitted from 1960 and 1970 due to small sample sizes/large confidence intervals.

Figure 6: Within-College Major Wage Gaps across Gender-Race/Ethnicity Groups



Source: ACS 2009-2017.
Notes: Vertical line indicates maximum predicted wage gap across highest and lowest paying college major.

Figure 7: Oaxaca-Blinder Decomposition – Gender

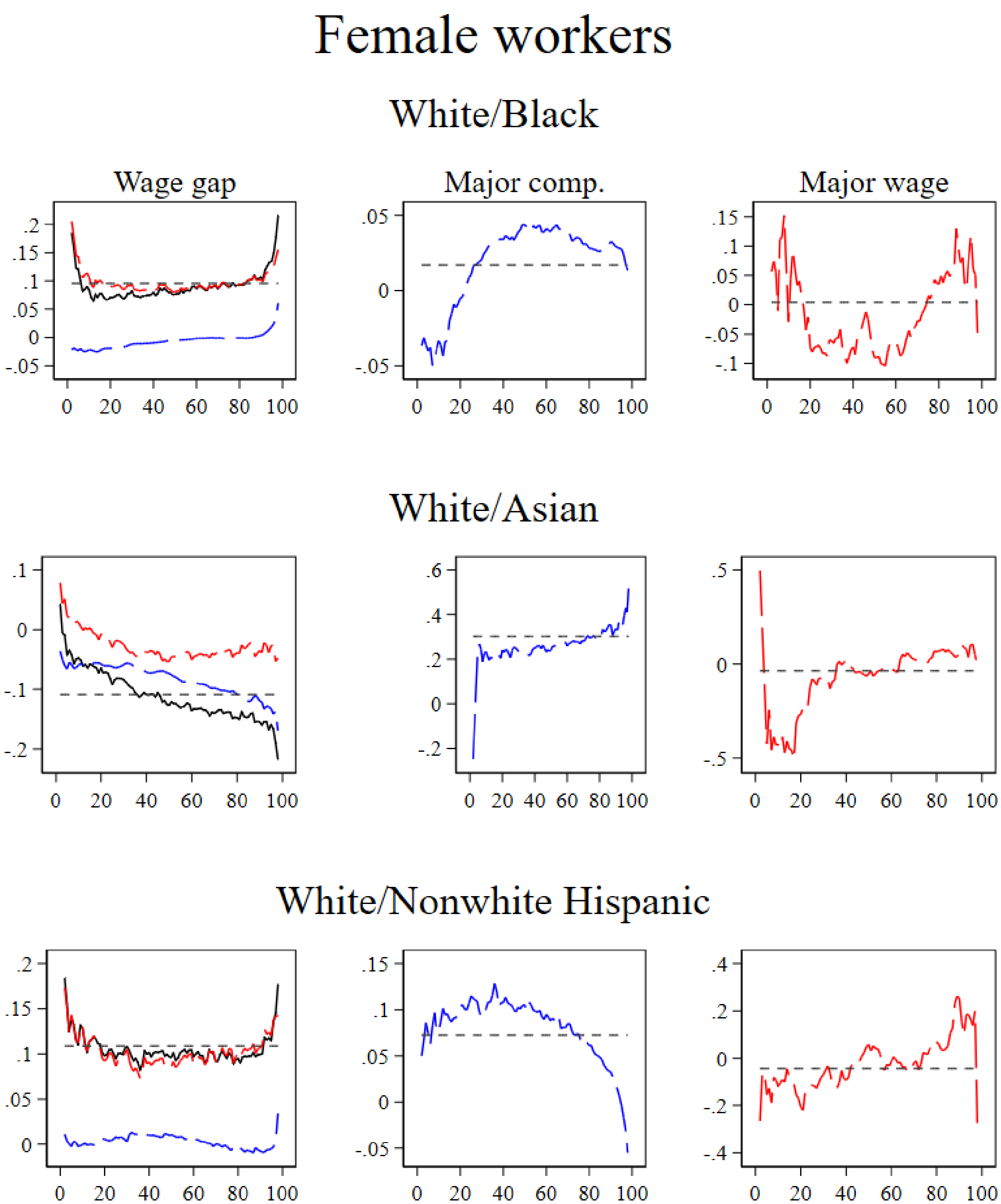


Source: ACS 2009-2017.

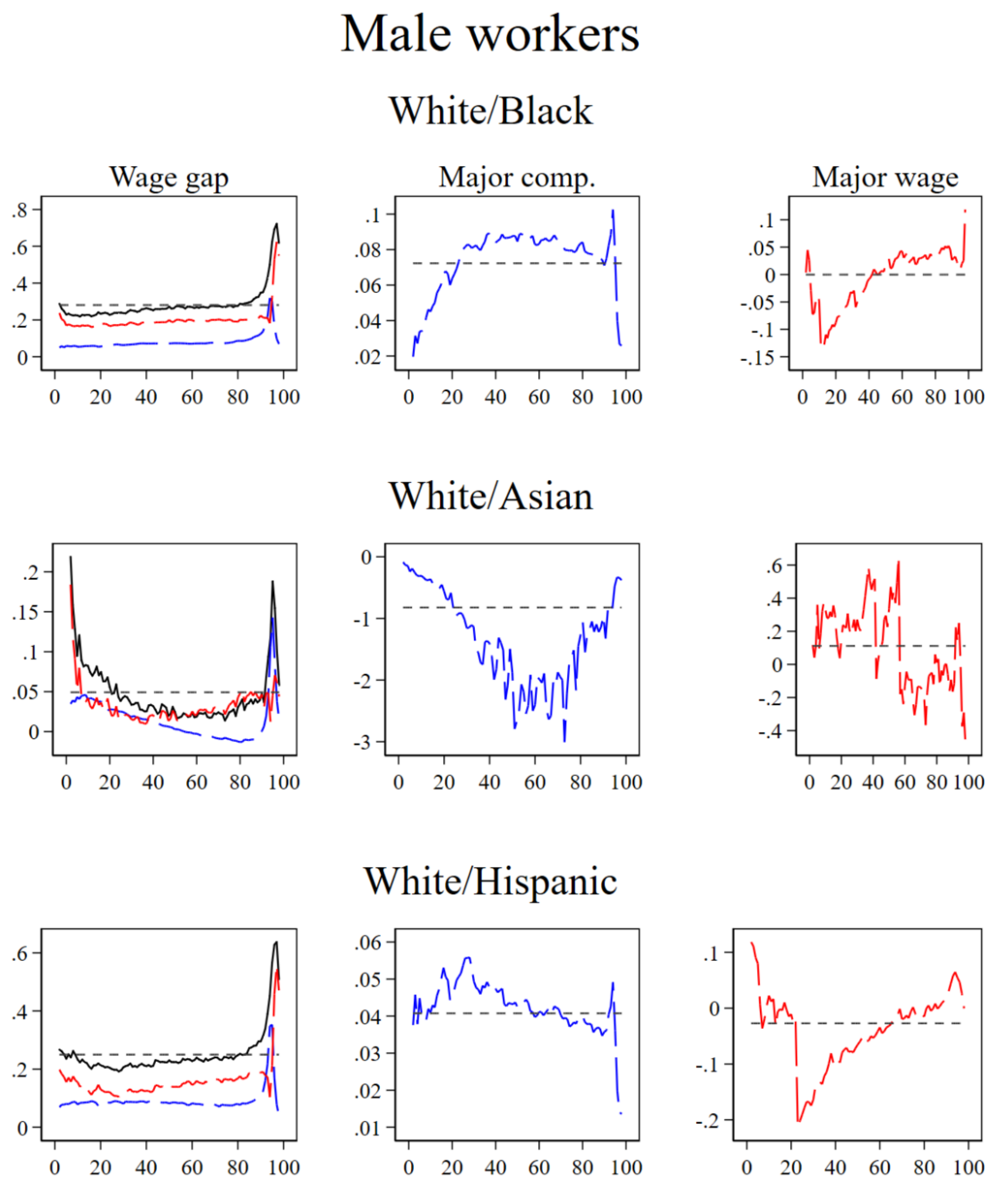
Notes: Left column: Black line = Wage gap at particular quantiles (2 through 98). Blue line = Explained portion due to composition differences. Red line = Unexplained portion due to wage effects. Y-axis = Log-wage gap between men and women at different quartiles. Middle column: Percent contribution of college major composition to overall gap. Right column: contribution of college major wage effects to total gap. In all panels, dashed horizontal lines show results from mean OB decomposition. Middle and right column y-axes visualize percent contribution of major composition / wage effect to observed gap. X-axes in all figures are wage quartiles.

Figure 8: Oaxaca-Blinder Decomposition – Race/Ethnicity

(A)



(B)



Source: ACS 2009-2017

Note: <u>Left column</u>: Black line = Wage gap at particular quantiles (2 through 98). Blue line = Explained portion due to composition differences. Red line = Unexplained portion due to wage effects. Y-axis = Log-wage gap between men and women at different quartiles. <u>Middle column</u>: Percent contribution of college major composition to overall gap. <u>Right column</u>: contribution of college major wage effects to total gap. In all panels, dashed horizontal lines show results from mean OB decomposition. Middle and right column y-axes visualize percent contribution of major composition / wage effect to observed gap. X-axes in all figures are wage quartiles.

Table 1: Summary statistics

	1960	1970	1980	1990	2000	2005-2009	2009-2017
Mean wage	2.89	3.19	3.08	3.14	3.02	3.36	3.32
wage variance	0.337	0.353	0.353	0.368	0.390	0.418	0.460
Female	27.22	29.31	36.76	44.00	48.31	50.25	52.13
White	94.06	93.53	91.26	89.61	87.63	85.15	82.14
Black	4.49	4.85	5.88	6.68	7.36	8.13	8.60
Asian	0.46	0.65	0.90	1.09	1.39	1.94	2.54
White Hispanic	0.10	0.15	0.33	0.35	0.47	0.49	0.47
Nonwhite Hispanic	0.86	0.80	1.50	1.55	2.16	2.96	4.28
Other	0.03	0.03	0.13	0.72	0.98	1.34	1.97
n	206,650	63,326	667,187	967,698	1,230,924	1,551,075	2,995,547

Sources: Census microdata and ACS.

Note: Sample includes non-self employed respondents with a bachelor's degree or more in the labor force, age 25-64, 400+ annual hours worked.

Table 2: Distribution of college majors

7 Category Major		37 Category Major				51 Category Major			
Major	Pct	Major	Pct	Major	Pct	Major	Pct	Major	Pct
Business (Bus)	21.77	Agriculture (Ag)	1.00	History (Hist)	2.19	Accounting (Acct)	3.70	International relations (IR)	0.25
Education (Educ)	12.22	Architecture (Arch)	0.62	Interdisciplinary and Multi-Disciplinary Studies (General) (Intr)	0.83	Agriculture and agricultural science (Ag)	1.00	Journalism (Journ)	0.98
Health (Health)	7.53	Area, Ethnic, and Civilization Studies (AEC)	0.33	Law (Law)	0.19	All other engineering (Engr)	2.38	Leisure studies and basic skills (Leis)	1.16
Liberal Arts (Larts)	11.59	Biology and Life Sciences (Bio)	4.48	Liberal Arts and Humanities (LAM)	1.46	Architecture (Arch)	0.62	Letters: literature writing other (LLWO)	4.53
Other (Other)	5.57	Business (Bus)	21.77	Library Science (LibS)	0.05	Area ethnic and civil studies (AECS)	0.33	Library science and education (LibS)	0.05
Social sciences (Socsci)	21.08	Communication Technologies (CTech)	0.14	Linguistics and Foreign Languages (Ling)	0.86	Art history and fine arts (ArtH)	1.30	Marketing (Mark)	2.47
STEM (STEM)	20.23	Communications (Com)	4.52	Mathematics and Statistics (Math)	1.25	Biological sciences (Bio)	4.51	Mathematics (Math)	1.27
		Computer and Information Sciences (Comp)	3.01	Medical and Health Sciences and Services (MHSS)	7.53	Business management and administration (Bus)	6.86	Mechanical engineering (MEngr)	1.34
		Construction Services (Cons)	0.21	Military Technologies (Milt)	0.01	Chemical engineering (ChemE)	0.47	Medical technology (MdTch)	0.34
		Cosmetology Services and Culinary Arts (Cosm)	0.09	Nuclear, Industrial Radiology, and Biological Technologies (Nucl)	0.03	Chemistry (Chem)	0.92	Miscellaneous business and medical support (Mbus)	7.01
		Criminal Justice and Fire Protection (Cj)	2.20	Philosophy and Religious Studies (Phil)	0.67	Civil engineering (CivE)	0.78	Multidisciplinary or general science (Multi)	1.24
		Education Administration and Teaching (Educ)	12.22	Physical Fitness, Parks, Recreation, and Leisure (PFPR)	1.07	Commercial art and design (Cart)	0.92	Music and speech/drama (Music)	1.26
		Electrical and Mechanic Repairs and Technologies (Elct)	0.03	Physical Sciences (PhysS)	2.63	Communications (Comm)	3.68	Nursing (Nurse)	4.16
		Engineering (Engr)	6.37	Psychology (Psyc)	5.08	Computer and information technology (Comp)	1.15	Other medical/health services (Health)	2.49
		Engineering Technologies (EgTch)	0.74	Public Affairs, Policy, and Social Work (PAPS)	1.56	Computer programming (CProg)	1.86	Other social science (SocSci)	3.12
		English Language, Literature, and Composition (Eng)	3.08	Social Sciences (SS)	7.41	Earth and other physical sciences (Earth)	0.52	Other (Other)	0.56
		Environment and Natural Resources (Env)	0.72	Theology and Religious Vocations (Thlg)	0.61	Economics (Econ)	1.75	Philosophy and religion (Phil)	1.28
		Family and Consumer Sciences (Fam)	0.81	Transportation Sciences and Technologies (Tran)	0.32	Electrical engineering (EEng)	1.40	Physics (Phys)	0.39
		Fine Arts (FA)	3.93			Engineering technology (EngrT)	0.77	Political science (PS)	2.47
						Environmental studies (Env)	0.72	Protective services (Prot)	2.21
						Family and consumer science (FCS)	0.81	Psychology (Psych)	5.08
						Film and other arts (Film)	0.44	Public administration and law (Law)	0.42
						Finance (Fin)	2.10	Public health (Phealth)	0.18
						Fitness and nutrition (Nutr)	0.18	Secondary education (SEduc)	12.22
						Foreign language (Lang)	0.86	Social work and human resources (SWrk)	1.32
						History (Hist)	2.19		

Data source: 2009-2017 American Community Survey (ACS). Respondents in labor force, age 25-64, with a Bachelor's degree or more, 400+ annual hours worked.
n=2,995,547

Table 3: Gender wage gap over time, by race/ethnicity

	1960					2011-15				
	Average	10th pctl	50th pctl	90th pctl	95th pctl	Average	10th pctl	50th pctl	90th pctl	95th pctl
White native born	-.17***	-.13***	-.16***	-.21***	-.23***	-.20***	-.13***	-.2***	-.29***	-.49***
	(0.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)
Black native	.01	-.03	.01	.04*	.02	-.08***	-.03*	-.06***	-.13***	-.15***
	(0.01)	(.03)	(.01)	(.02)	(.02)	(0.01)	(.01)	(.01)	(.01)	(.01)
Asian native born	-.06	.06	-.12**	-.09*	-.06	-.09***	-.02	-.09***	-.17***	-.26***
	(.04)	(.12)	(.04)	(.04)	(.05)	(.01)	(.02)	(.01)	(.01)	(.02)
Other native born	-.15***	-.09	-.18***	-.17**	-.14**	-.15***	-.08***	-.14***	-.21***	-.26***
	(.04)	(.1)	(.04)	(.05)	(.05)	(.01)	(.01)	(.01)	(.01)	(.02)
White Hispanic native born	.21	-.44	.03	.97	.15	-.11***	-.05*	-.12***	-.13***	-.17***
	(.5)	(.79)	(.34)	(1.33)	(1.02)	(.01)	(.02)	(.01)	(.02)	(.02)
Nonwhite Hispanic native born	.01	.27	-.06	-.15	-.67*	-.15***	-.09*	-.09***	-.24***	-.3***
	(.11)	(.3)	(.11)	(.19)	(.32)	(.02)	(.04)	(.02)	(.03)	(.05)
Overall	-.16***	-.11***	-.16***	-.18***	-.21***	-.19***	-.11***	-.19***	-.27***	-.41***
	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)

* p<0.05 **p<0.01 ***p<0.001, two-tailed tests

Cells represent the wage difference between male and female college educated workers, separately by group.

Coefficient represent the adjusted wage gap between male and female workers net of a quartic function of age, binary indicator of over 5 years of college, 19 industry fixed effects, government worker indicator, marital status interacted with presence of one's own children in the household, whether the respondent has a young child in the household, the number of children, whether the respondent lives in a metropolitan area, and state fixed effects

Robust standard errors in parentheses

“Average” column estimated by OLS regression with robust standard errors. “Pctl” columns come from recentered influence regression models estimated at particular quantiles of the unconditional wage distribution.

Table 4: Race/ethnicity wage gap over time, by gender

	1960					2011-15				
Women										
	Average	10th pctl	50th pctl	90th pctl	95th pctl	Average	10th pctl	50th pctl	90th pctl	95th pctl
Black	-.06***	-.22***	-.06***	0	.03**	-.10***	-.1***	-.08***	-.1***	-.11***
	(.01)	(.04)	(.01)	(.01)	(.02)	(.01)	(.01)	(.01)	(.01)	(.01)
Asian	-.02	.29**	-.02	-.03	-.04	.06***	.02	.07***	.1***	.12***
	(.03)	(.04)	(.01)	(.01)	(.02)	(.01)	(.01)	(.01)	(.01)	(.01)
Other	-.03	-.03	-.03	.01	.06	-.07***	-.08***	-.06***	-.07***	-.08***
	(.02)	(.04)	(.01)	(.01)	(.02)	(.01)	(.01)	(.01)	(.01)	(.01)
White Hispanic	.00	-.1	.08	.11	.36	-.11***	-.13***	-.1***	-.09***	-.1***
	(.10)	(.04)	(.01)	(.01)	(.02)	(.01)	(.01)	(.01)	(.01)	(.01)
Nonwhite Hispanic	.00	-.07	-.01	.03	.03	-.09***	-.17***	-.08***	-.06***	-.07***
	(.05)	(.04)	(.01)	(.01)	(.02)	(.01)	(.01)	(.01)	(.01)	(.01)
Men										
	Average	10th pctl	50th pctl	90th pctl	95th pctl	Average	10th pctl	50th pctl	90th pctl	95th pctl
Black	-.27***	-.5***	-.28***	-.17***	-.14***	-.21***	-.23***	-.22***	-.21***	-.26***
	(.01)	(.02)	(.01)	(.01)	(.02)	(.01)	(.01)	(.01)	(.01)	(.02)
Asian	-.08***	-.13*	-.07**	-.12***	-.09**	.01	-.01	.03***	-.02	-.01
	(.02)	(.02)	(.01)	(.01)	(.02)	(.01)	(.01)	(.01)	(.01)	(.02)
Other	-.05***	-.07	-.07***	.03	-.01	-.11***	-.12***	-.11***	-.13***	-.16***
	(.01)	(.02)	(.01)	(.01)	(.02)	(.01)	(.01)	(.01)	(.01)	(.02)
White Hispanic	-.22***	-.29	-.29***	-.12	-.13**	-.17***	-.23***	-.17***	-.18***	-.2***
	(.06)	(.02)	(.01)	(.01)	(.02)	(.01)	(.01)	(.01)	(.01)	(.02)
Nonwhite Hispanic	-.18***	-.31	-.23***	-.06	-.1	-.15***	-.25***	-.13***	-.08***	-.1*
	(.05)	(.02)	(.01)	(.01)	(.02)	(.04)	(.01)	(.01)	(.01)	(.02)

* p<0.05 **p<0.01 ***p<0.001, two-tailed tests
Cells represent the wage difference between listed group and native born white group.
Adjusted cells are the predicted wage gap between male and female workers net of a quartic function of age, binary indicator of over 5 years of college, 19 industry fixed effects, government worker indicator, marital status interacted with presence of one's own children in the household, whether the respondent has a young child in the household, the number of children, whether the respondent lives in a metropolitan area, and state fixed effects
Robust clustered standard errors in parentheses
"Average" column estimated by OLS regression with robust standard errors. "Pctl" columns come from recentered influence regression models estimated at particular quantiles of the unconditional wage distribution.