Racial and Ethnic Earnings Gaps among Skilled Workers: The Role of Fields of Study and Occupations*

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Abstract

Although education is generally perceived as a tool to reduce racial and ethnic disparities, substantial earnings gaps are observed across White, Black and Hispanic workers with university degrees. Using data on U.S.-born college graduates from the American Community Survey for the years 2009-2021, we examine the extent to which differences in field of study and occupational sorting account for these gaps. We find that differences in field of study account for only a modest portion of the overall disparities. Black and Hispanic workers, however, tend to work in lower-paying occupations compared to White workers with the same detailed field of study background. Using information from O*NET, we show that Black and Hispanic workers tend to be more concentrated in occupations that require routine and contact tasks, and less concentrated in occupations that involve analytical and managerial tasks, as compared to White worker with degrees in the same field of study. While these differences play an important role in accounting for the racial and ethnic earnings gap, the largest share of the gap is observed among individuals who majored in the same detailed field of study and are working in the same detailed occupation. We explore the extent to which unequal rewards for the same skills can explain these gaps.

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1 Introduction

Racial and ethnic earnings gaps are a persistent feature of the U.S. labor market. Progress in closing the Black-White and the Hispanic-White earnings gaps has been relatively limited since the 1980s (Bayer & Charles, 2018; Collins & Moody, 2018; Antman et al., 2023; Bayer et al., 2025). Economic shocks and structural changes, such as the Great Recession (Hoynes et al., 2012), the COVID-19 pandemic (Cortes & Forsythe, 2023; Gambau et al., 2022), and the rise of automation (Dicandia, 2021; Gray et al., 2024), have disproportionately impacted Black and Hispanic workers. Although differences in education can partially explain these patterns, considerable earnings gaps are observed even among skilled workers.

In this paper, we study the role of fields of study and occupations in accounting for the earnings gap between Black, Hispanic and White skilled workers in the U.S. We focus on U.S.-born college graduates who are working full-time throughout the year. Using data from the American Community Survey (ACS) for the years 2009–2021, we first show that Black and Hispanic workers in this highly-selected group earn around 22% and 15% less than their White counterparts, respectively. We then explore the extent to which these gaps can be attributed to differences in field of study choices, and to differences in occupational outcomes conditional on field of study. We leverage the fact that the ACS provides detailed information on individuals' undergraduate major (coded across 170 fields of study) and their occupation (coded across 479 occupational categories).

After controlling for a host of observable characteristics, we find that differences in field of study composition account for a modest fraction of the gap in residual earnings between White workers and workers from minority backgrounds—around 10-14%. In contrast, differences in the occupational composition of employment conditional on field of study account for a larger share—between 30-40%—of the within-major residual earnings gap. In other words, Black and Hispanic workers are disproportionately concentrated in lower-paying occupations, as compared to their White counterparts with degrees in the same fields of study. This occupational downgrading is particularly pronounced among graduates from high-income majors. Nonetheless, even after considering both field of study and occupation, over 60% of the earnings differential remains unexplained, indicating that there are large disparities in earnings between

White and minority workers who majored in the same detailed field of study and are working in the same detailed occupation.

To shed further light on these patterns, we draw on O*NET data on the task and skill requirements of different occupations. We characterize occupations along seven dimensions, which we refer to as skill clusters: Routine, Analytical, Social, Physical, Contact, Communication, and Managerial. We explore the dimensions along which the occupations that Black and Hispanic individuals disproportionately work in differ in. We find that, conditional on their field of study, Black and Hispanic individuals tend to be more concentrated in occupations that require Routine and Contact tasks, and less concentrated in occupations that involve Analytical and Managerial tasks, as compared to their White counterparts.

Following Manuel & Plesca (2020), we also construct a measure of the "potential skills" of each individual based on their field of study and the characteristics of the occupations that each specific field of study typically prepares its graduates for, as determined by experts at the Bureau of Labor Statistics and the National Center for Education Statistics. We find that Black and Hispanic workers end up in occupations in which their Analytical, Social, Communication, and Managerial skills are underutilized.[1] We also explore the extent to which unequal rewards for skills can explain the observed earnings gaps within field of study-occupation cells.

Our findings help broaden our understanding of the factors underlying the observed racial and ethnic earnings gaps among skilled workers. By doing so, we contribute to a vast literature studying racial and ethnic inequality, much of which was recently overviewed by Bayer et al. (2025). It has been well established that demographic controls alone do not fully explain the gaps in earnings between White and minority workers. A central issue in this literature is the extent to which differences in skills can account for the observed gaps (e.g. Neal & Johnson, 1996; Carneiro et al., 2005; Lang & Manove, 2011).

Naturally, an individual's level of education is only a rough proxy of their skill level. By focusing on fields of study, we can begin to unpack the potential reasons for the observed earnings gaps between White and minority workers with the

[1]This result complements and extends the evidence of Lu & Li (2021), who show that overeducation is substantially more prevalent among minority workers, i.e. minority workers are more likely to have a higher level of education than what their occupation requires.

same (high) level of education. Field of study choices reflect differences in skills and preferences, and have important implications for subsequent labor market outcomes (Altonji et al., 2016a,b; Patnaik et al., 2021). As discussed by Sloane et al. (2021), analyzing differences in fields of study choices across demographic groups can help us understand the extent to which earnings gaps are predetermined by sorting that happens before workers enter the labor market. While the role of fields of study has been more extensively studied in the context of the gender wage gap—Sloane et al. (2021) being a notable example—evidence with regards to their role in accounting for racial and ethnic wage gaps is scarce, and based on relatively small surveys such as the 1993 National Survey of College Graduates (Black et al., 2006), the 1995 Survey of Recent College Graduates (Weinberger, 1998), or the Baccalaureate and Beyond study (Zhang, 2008).[2] Our analysis contributes to the literature by providing evidence of the importance of field of study choices using the large nationally-representative survey data from the ACS. Our focus on outcomes for U.S.-born Hispanics also fills a gap in the literature highlighted by Antman et al. (2023).

Another contribution of our paper is to explore the role of occupational sorting conditional on field of study. Earnings differences across occupations have been well documented (e.g. Erosa et al., 2024). While several studies have explored the importance of occupational sorting in accounting for racial wage gaps (e.g. Huffman & Cohen, 2004; Collins & Moody, 2018; Alonso-Villar & del Río, 2023; Jardina et al., 2023; Gray et al., 2024), there is little evidence on the extent to which these differences in occupational sorting are driven by differences in field of study composition, or by heterogeneous degrees of mismatch conditional on field of study.[3] This is in spite of the fact that the link between fields of study and occupations has been shown to be important for the average worker, with those employed in occupations that are closely aligned to their field of study earning significantly higher wages than those employed in "out-of-field" jobs (Lemieux, 2014; Manuel, 2024; Cassidy & Gaulke, 2024).

[2]Evidence on the importance of field of study choices in accounting for racial wage gaps in Brazil is presented in Reis (2017). Several papers focus specifically on STEM fields, and in particular on the persistence probabilities of minority workers in STEM, e.g. Griffith (2010); Arcidiacono et al. (2016).

[3]The limited evidence that considers the joint roles of fields of study and occupations for racial gaps is also based on relatively small samples, such as the 2003 National Survey of College Graduates in the case of McClough & Benedict (2017).

In order to further understand the role of differences in fields of study and occupations, we also draw on the literature pioneered by Autor et al. (2003), which characterizes occupations according to their task content. As highlighted by Hurst et al. (2024), one of the main benefits of the task-based approach is the fact that it reduces the dimensionality of the occupational data from a large number of detailed occupational codes to a small number of common tasks or skills. Our findings complement those of Golan & Sanders (2019), Hurst et al. (2024) and Gray et al. (2024) by focusing on skilled workers and considering their field of study choices, thus allowing us to investigate the mismatch between the "potential skills" that individuals from different racial and ethnic backgrounds acquire through their studies (along the lines of Manuel & Plesca, 2020), and the "actual skills" required in the occupations that they work in.

2 Data and Summary Statistics

Our primary dataset is the American Community Survey (ACS), as made available by IPUMS (Ruggles et al., 2025). We use data for 2009–2021, the years for which detailed information on individuals' field of study is available. We exclude observations with imputed values for key demographic and employment variables,[4] and following Sloane et al. (2021), we adjust the survey weights based on the predicted probability than an individual's data is complete given their demographic characteristics.[5]

We restrict our analysis to individuals aged 22–64 who have a bachelor's degree or above. To abstract from considerations related to part-time work, we focus only on individuals who are employed full-time, full-year, defined as those who usually worked at least 35 hours per week and 40 weeks per year (as in Acemoglu & Autor, 2011). Moreover, to abstract from considerations related to immigration status, we focus only on U.S.-born individuals. We classify individuals into four mutually exclusive race/ethnicity groups: Non-Hispanic White, Non-Hispanic Black, Hispanic, and all

[4]Specifically: age, sex, race, Hispanic origin, educational attainment, field of study, usual hours worked per week, weeks worked per year, and annual wage income.

[5]Specifically, we estimate the probability of an individual's data being complete based on their age, sex, race/ethnicity and place of birth, using a Logit model, and we then compute an adjusted individual-level weight by multiplying the survey weight provided in the data with the inverse of the predicted probability of having a complete record.

others (including those reporting more than one race). For simplicity, we refer to these groups as White, Black, Hispanic, and Other.

To gauge the importance of our restrictions for the racial and ethnic composition of our analysis sample, Table 1 provides information on the share of individuals from each of the four racial and ethnic groups across four subsamples: (1) all individuals aged 22-64; (2) the subset of these who are U.S.-born; (3) the subset of these who hold at least a Bachelor's degree; and (4) the subset of these who are employed full-time full-year.

Column (2) shows that conditioning on U.S.-born individuals substantially reduces the share of Hispanics relative to the general population, as one might expect given the large proportion of Hispanic individuals who were born abroad. Approximately one-third of U.S.-born individuals aged 22-64 hold a Bachelor's degree or higher, as the change in sample size between Columns (2) and (3) indicates. The fraction of Black individuals decreases from 13.1% in Column (2) to 8.0% in Column (3). The corresponding shares for Hispanic individuals are 9.0% and 5.7%. This reflects the fact that (U.S.-born) Black and Hispanic individuals are less likely to hold a Bachelor's degree (or higher), compared to White individuals. Finally, Column (4) shows that further restricting to individuals working full-time full-year (our final analysis sample) does not induce major additional changes in the racial and ethnic composition of the sample.

Our key measure of earnings is individuals' annual wage and salary income, which we convert to real 2021 dollars using the Bureau of Labor Statistics' Consumer Price Index for all urban consumers (CPI-U). Our main goal is to understand the role of fields of study and occupations in accounting for racial and ethnic earnings gaps among our sample of skilled, full-time full-year workers. The ACS data distinguishes between 170 fields of study, and 479 occupations.[6] The field of study variable captures the field in which the person received their Bachelor's degree (even if they have a higher degree such as a Master's or a PhD). Individuals can report up to two fields of study.

[6]The detailed degree field category (*degfieldd*) contains 177 categories, which change slightly over time. To ensure consistency across years, we harmonize the codes, leaving us with 170 unique degree fields. For occupations, we use the *occ2010* variable, which is coded consistently throughout our sample period.

Table 2 provides summary statistics for individuals in our analysis sample, overall, and broken down by race/ethnicity. Black and Hispanic workers are slightly younger, on average, than White workers in our sample. The proportion of female workers is highest among Black individuals, reflecting the larger gender gap in higher education attainment (in favor of women) within this group. Black workers are disproportionately located in the South, and Hispanics in the West. Around 11% of workers in our sample report having Bachelor's degrees in two fields. Moreover, slightly more then one-third of the individuals in our sample have a graduate degree.

The table also shows that there are large earnings differences between White, Black and Hispanic individuals in our sample. Despite focusing only on skilled, U.S.-born, full-time, full-year workers—a sample that is particularly positively selected among Black and Hispanic individuals, as shown in Table 1—the bottom rows of Table 2 indicate that White individuals earn around $104,000 per year on average, whereas average earnings for Black and Hispanic workers are around $78,000 and $85,000, or around 74.5% and 81.7% of White workers' average earnings, respectively. For reference, average earnings of Black and Hispanic workers in the general U.S.-born workforce (i.e. not restricting on having higher education or working full-time full-year) are around 71.3% and 75.8% of those of White workers, respectively. Thus, perhaps surprisingly, average earnings gaps in this highly selected sample of skilled, full-time full-year workers are not substantially smaller than among the general U.S.-born workforce.

In order to account for differences in observable demographic and geographic characteristics across individuals from different racial and ethnic backgrounds in our sample, we compute residual earnings by estimating a Mincerian log earnings regression, with controls for sex, age and age squared, interaction terms between these variables, indicator variables for marital status, education level, and for reporting two BA degree fields, and a set of fully interacted commuting zone-by-year fixed effects.[7]

Panel A of Figure 1 illustrates the raw gap in log real annual earnings for Hispanic and Black workers, relative to White workers. Panel B plots the corresponding gaps in residual earnings. After accounting for demographic characteristics, education levels, and detailed location of residence, substantial earnings gaps persist, of around 9% for

[7]Each individual's commuting zone is assigned using the crosswalk file from Autor & Dorn (2013).

Hispanic workers, and 15% for Black workers. Panels C and D compute the residual earnings gap separately by sex. The gaps are more pronounced among men than women, but are substantial for both groups.

Figure 2 plots the evolution of the residual earnings gaps across birth cohorts. We group individuals according to their birth year (imputed based on the year of the survey and the individual's age) into 5-year bins, from those born in 1950-1954 to those born in 1990-1994. The figure shows that the Hispanic–White earnings gap is fairly stable across birth cohorts, at around 10%. The Black-White earnings gap, meanwhile, shows some signs of shrinking across cohorts, from around 20% among those born in 1955-1959, to around 12% among those born in 1990-1994.

3 The Role of Fields of Study

We begin by analyzing the extent to which the racial and ethnic earnings gaps among skilled workers that we have documented above can be explained by differences in their field of study choices.

As a first approach, we generate a simple measure of the earnings potential of each of the 170 distinct fields of study included in the dataset. Along the lines of Sloane et al. (2021), we do this by computing the median earnings in each field of study among White males aged 43 to 57 (a group that can be assumed to face minimal post-educational frictions in the labor market). We then rank all fields according to this measure, and group them into employment-weighted quartiles, which we label as Low, Medium-Low, Medium-High, and High Income majors. Appendix Table A.1 lists all detailed fields of study, showing their measure of earnings potential, as well as the income group that we assign them to. Disciplines such as Philosophy, Sociology, Humanities, and Religious Studies fall into the lowest-income group. The Medium-Low income group includes fields such as Criminology, Geology, History, English and Foreign Languages. Examples of majors from the Medium-High income group are Architecture, Business Management and Administration, Mathematics, and some Engineering fields. Lastly, the highest-income group consists of majors such as Neuroscience, Actuarial Science, Computer Science, and Finance.

Figure 3 plots the difference in the proportion of Black and Hispanic individuals

in each of the four major groups, relative to White workers.[8] The figure shows that the proportion of Black and Hispanic individuals who hold degrees in low-paying majors is very similar to the corresponding proportion among White workers. Black and Hispanic workers, however, are less likely to hold degrees in high-income majors, and more likely to hold degrees in middle-paying majors. In particular, the share of workers who hold a degree in high income (top 25%) fields of study is approximately 7 percentage points lower for Black workers, and 4 percentage points lower for Hispanic workers.

To fully investigate the role of differences in field of study composition in accounting for the observed earnings gaps for minority workers, we implement a decomposition analysis. Specifically, we can express the average residual earnings of individuals from group g, $\bar{w}^g$, as:

$$\bar{w}^g = \sum_m s_m^g \bar{w}_m^g \ ,$$

where g represents a particular race/ethnicity group, s_m^g represents the share of individuals from group g whose Bachelor's degree is in detailed field of study (or major) m, and $\bar{w}_m^g$ represents the average residual earnings of individuals from group g whose Bachelor's degree is in field of study m.

We can decompose the gap between the average residual earnings of workers from minority backgrounds and White workers, as follows:

$$\bar{w}^g - \bar{w}^W = \sum_m \bar{w}_m^W (s_m^g - s_m^W) + \sum_m s_m^g (\bar{w}_m^g - \bar{w}_m^W) \ , \tag{1}$$

where g represents either Black or Hispanic workers, while W denotes White workers. The first term on the right-hand-side of Equation (1) quantifies the role of differences in field of study (the *sorting* component), assuming all workers are paid the same as White workers, conditional on their field of study. The second term quantifies the role of differences in pay between White and minority workers conditional on field of study (the *within major* component).

As usual with these types of decompositions, one can also implement the analysis using minority workers' earnings within fields as the reference for quantifying the

[8]For individuals who report two fields of study, we assign them the one with the higher earnings potential.

sorting component, i.e.:

$$\bar{w}^g - \bar{w}^W = \sum_m \bar{w}^g_m (s^g_m - s^W_m) + \sum_m s^W_m (\bar{w}^g_m - \bar{w}^W_m) \ . \tag{2}$$

We implement the decompositions in Equations (1) and (2) using the 170 detailed fields of study available in the ACS. Panel A of Table 3 presents the results. Column (1) reproduces the total residual earnings gap, which was shown in Panel B of Figure 1. Columns (2) and (3) show the result based on Equation (1), which uses White workers as the reference earnings group. Based on this decomposition, less than 10% of the Black-White gap and around 15% of the Hispanic-White gap can be attributed to differences in field of study composition (sorting). The vast majority of the gap is attributable to differences in (residual) earnings between White and minority workers *within* fields of study. The results in Columns (4) and (5), which use minority workers as the reference earnings group, as in Equation (2), attribute a slightly larger fraction of the gap to differences in field of study composition. However, even in this case over 85% of the overall earnings gap is observed across workers within the same detailed field of study. This share is slightly higher than the corresponding shares found for the gender earnings gap in Sloane et al. (2021), which ranges between 72-82%.

Panel B presents results for the sample of individuals who hold a Bachelor's degree only (i.e. excluding those with further education such as a Master's degree or a PhD). Overall, the results are quite similar in this sample, indicating that the findings are not driven by those with the highest levels of education.

Appendix Table A.2 presents analogous decomposition results across subgroups defined by sex and birth cohort. Among both men and women, and among older as well as younger cohorts, earnings differences conditional on field of study play a much more important role than field of study composition differences in accounting for the observed earnings gaps for minority workers relative to White workers. Sorting across fields of study plays a somewhat more important role among older birth cohorts (those born between 1955 and 1974) for both Hispanic–White and Black–White wage gaps. This indicates that older cohorts of White and minority undergraduates tended to sort into a more heterogeneous set of majors (in terms of pay) as compared to younger cohorts. Nonetheless, even among these older cohorts the differences in field of study

composition account for less than one-fifth of the overall residual earnings gap.

Figure 4 allows us to visualize the within-field-of-study earnings gaps between White and minority workers. Each dot on the graph corresponds to a detailed field of study. The fields have been ranked along the x-axis according to their potential earnings, measured as discussed above. The y-axis indicates the magnitude of the difference in mean residual earnings between Black and White workers (Panel A) or between Hispanic and White workers (Panel B) within each field. The figure shows that minority workers earn less than White workers within almost all fields of study. Moreover, the figure clearly indicates that the gaps are particularly pronounced among individuals who majored in higher-paying fields of study.

4 Occupational Sorting and Earnings Gaps Conditional on Field of Study

The results in the previous section indicate that racial and ethnic earnings gaps are primarily driven by differences in earnings among graduates from the same fields of study. To further understand these gaps, we explore the extent to which minority workers are employed in different occupations than their White peers with the same field of study background. We do this by implementing a further decomposition of the "within major" earnings gap.

First, note that average residual earnings among workers from group g holding a degree from major m can be expressed as follows:

$$\bar{w}_m^g = \sum_o s_{o|m}^g \bar{w}_{o|m}^g \ ,$$

where $s_{o|m}^g$ is the number of workers from group g who hold a degree in field m and work in occupation o, as a fraction of the total number of workers from group g who hold a degree in field m, and $\bar{w}_{o|m}^g$ are the average (residual) earnings of workers from group g who hold a degree in field m and work in occupation o.

Given this definition, the difference in residual earnings between workers from

minority group g and White workers can be decomposed as follows:

$$\bar{w}_m^g - \bar{w}_m^W = \sum_o \bar{w}_{o|m}^W \left(s_{o|m}^g - s_{o|m}^W\right) + \sum_o s_{o|m}^g \left(\bar{w}_{o|m}^g - \bar{w}_{o|m}^W\right) . \tag{3}$$

The first component on the right-hand-side of Equation (3) captures differences in the occupational employment distribution of minority workers relative to White workers, conditional on holding a degree in major m. The second component captures racial and ethnic differences in (residual) earnings conditional on field of study *and* occupation.

As before, the decomposition can alternatively be expressed using the earnings of minority workers (within major and occupation) as a reference, i.e.:

$$\bar{w}_m^g - \bar{w}_m^W = \sum_o \bar{w}_{o|m}^g \left(s_{o|m}^g - s_{o|m}^W\right) + \sum_o s_{o|m}^W \left(\bar{w}_{o|m}^g - \bar{w}_{o|m}^W\right) . \tag{4}$$

We can sum the major-specific terms in Equations (3) and (4) across majors using the same weights as in the "within major" components in Equations (1) and (2), i.e.:

$$\sum_m s_m^g \left(\bar{w}_m^g - \bar{w}_m^W\right) = \sum_m s_m^g \sum_o \bar{w}_{o|m}^W \left(s_{o|m}^g - s_{o|m}^W\right) + \sum_m s_m^g \sum_o s_{o|m}^g \left(\bar{w}_{o|m}^g - \bar{w}_{o|m}^W\right) , \tag{5}$$

or alternatively:

$$\sum_m s_m^W \left(\bar{w}_m^g - \bar{w}_m^W\right) = \sum_m s_m^W \sum_o \bar{w}_{o|m}^g \left(s_{o|m}^g - s_{o|m}^W\right) + \sum_m s_m^W \sum_o s_{o|m}^W \left(\bar{w}_{o|m}^g - \bar{w}_{o|m}^W\right) . \tag{6}$$

These equations allow us to decompose the "within major" components from Equations (1) and (2) into an *occupational sorting* component conditional on major—the first term on the right-hand-side of Equations (5) and (6)—and a component driven by earnings differences among workers with degrees in the same field of study and working in the same occupation—the second term on the right-hand-side of Equations (5) and (6).

We implement the decompositions in Equations (5) and (6) using detailed fields of study (170 categories) and using detailed occupation codes (479 categories from *occ2010*). The results are shown in Table 4. We find that roughly one-third to two-

fifths of the "within major" earnings gap between workers from minority backgrounds and White workers in our sample can be attributed to occupational sorting, i.e. differences in the occupational distribution of employment conditional on field of study. The remainder of the gap is due to earnings differences between minority workers and White workers who hold a degree in the same detailed field of study and work in the same detailed occupation.[9]

To further understand the differences in occupational sorting conditional on field of study, we group the detailed occupational categories into four broad income tiers based on each occupation's earnings potential. As before, we measure earnings potential using the median earnings of White males aged 43–57, and create four groups comprising roughly 25% of aggregate employment each, ranging from low- to high-paying occupations. Table 5 indicates the differences in occupational sorting conditional on field of study for minority workers relative to White workers. Each cell shows the percentage point difference between the share of workers from a given field of study group that are employed in a given occupational income group among Black/Hispanic workers, and the corresponding share for White workers.

Consistent with the finding that occupational sorting partially accounts for the observed earnings gaps within majors (Table 4), we find that minority workers are disproportionately employed in lower-income occupations, even when compared to White workers with degrees in the same fields of study. These differences in occupational sorting are observed throughout the distribution of majors and hence are not concentrated among individuals majoring in specific fields. For example, the fraction of Black workers with degrees from high-income majors employed in high-income occupations is around 11 percentage points lower than the corresponding fraction for White workers. Black workers from low-income majors are also over-represented in low-income occupations, by around 6 percentage points. For Hispanic workers, we observe qualitatively similar, albeit somewhat smaller gaps. Hence, regardless of major, White workers frequently achieve occupations that are more advantageous than their field of study alone would predict. Conversely, Black and Hispanic individuals often experience occupational downgrading, even with a high-income major.

Finally, we provide further analysis of the gaps in (residual) earnings observed

[9] Appendix Table A.3 shows broadly similar results when we break down the sample by sex or by birth cohort.

across workers with degrees in the same field of study and working in the same occupation, which we found to account for the majority of the residual earnings gaps within fields of study (Table 4). Table 6 shows the difference in mean residual earnings within different field of study-occupation cells. These earnings gaps are substantial, especially within higher-paying occupations. For example, Black workers with degrees from high-income majors who are working in high-paying occupations earn about 16% less than White workers (after controlling for observable demographic and geographic characteristics). For Hispanic workers, the corresponding figure is around 10%. Hence, not only are minority workers less likely to work in higher-paying occupations conditional on their field of study, but when they do work in these occupations they earn significantly less than their White counterparts.

5 Link to Occupational Skills and Tasks

To deepen our understanding of the patterns that we have documented above, we supplement the ACS data with information from O*NET (the Occupational Information Network). O*NET provides detailed occupation-level information on the skills that workers require and the tasks that they typically perform in their occupation.

5.1 O*NET Data

We use data from O*NET version 20.1 (National Center for O*NET Development, 2015), and characterize occupations along seven key dimensions based on information from the Skills, Abilities, Knowledge, Work Context and Work Activities modules in O*NET. For simplicity, we refer to the seven dimensions as *skill clusters*.

The first three clusters are drawn from Deming (2017). They capture the extent to which an occupation involves *Routine* tasks, i.e. tasks that are algorithmic in nature and therefore relatively easy to automate (Autor et al., 2003); the *Analytical* content of an occupation (measured based on the importance of mathematical skills and knowledge); and the importance of *Social* or interpersonal skills (based on the importance of skills related to social perceptiveness, negotiation, persuasion, and coordination). Our fourth cluster is drawn from Cortes et al. (2023), and captures

the importance of *Physical* abilities. Following Hurst et al. (2024), the fifth cluster that we consider is the extent to which the occupation involves *Contact* tasks, namely contact with others, and dealing with external customers or the public in general. Finally, we consider two new dimensions: the importance of basic *Communication* skills, and the extent to which the occupation is *Managerial* in nature (i.e. the extent to which it involves leadership and decision-making tasks). Table 7 provides a detailed mapping of the O*NET elements included in each of these clusters.

Each O*NET element is first rescaled to range from 0 to 10. We then calculate the unweighted mean of the elements that we assign to each cluster, to create a cluster-level score for each detailed (8-digit) O*NET occupation code.[10] These occupation codes are a more detailed version of the 2010 Standard Occupation Classification (SOC) codes. We create a score for each 6-digit SOC code by computing a simple average across all of the 8-digit codes that fall within the same 6-digit SOC code.

To assign skill cluster scores from O*NET to each *occ2010* code in our data, we follow the same procedure as Cortes et al. (2023).[11] This process yields occupation-level skill scores for 475 detailed occupations.[12] We merge these scores into our ACS data, and standardize each skill cluster to have a mean of zero and a unit variance within the analysis sample.

We also compute skill cluster scores for each field of study. Following Manuel & Plesca (2020), we do this by taking advantage of a crosswalk from the National Center for Education Statistics (NCES) which maps fields of studies to occupations.[13] The purpose of the crosswalk is to indicate the occupations that require the skills and knowledge provided by particular programs of study. As described on the NCES website, the matches are based on the content of the field of study and the occupation code descriptions, combined with expertise from statisticians at the Bureau of Labor Statistics and the NCES.

[10] For elements that have both an importance and a level score, we first re-scale both scores to a common 0–10 scale, then take their average to obtain a single score for each skill element, and then average this with the other skill elements in the same cluster.

[11] This procedure uses SOC code-level employment information from the Bureau of Labor Statistics' Occupational Employment Statistics (OES) data for 2016, as well as crosswalks between SOC codes and *occ2010* codes from the U.S. Census Bureau.

[12] Four military occupations out of the 479 detailed occupations in our dataset are excluded because O*NET does not report skill data for these occupations.

[13] https://nces.ed.gov/ipeds/cipcode/post3.aspx?y=56

The NCES crosswalk codes fields of study according to the Classification of Instructional Programs (CIP), and codes occupations using SOC 2010 codes. The mapping is many-to-many: a given program may plausibly lead to several occupations. We first allocate our O*NET skill cluster scores to each SOC 2010 code. We then aggregate the skill cluster score to the CIP code level using the NCES crosswalk. When a particular field of study maps to multiple SOC 2010 occupations, we take a simple average of the scores of each of those occupations (since we do not have data at the SOC-by-CIP level in order to compute a weighted average). In a final step, we map CIP codes to the field of study codes in the ACS data (*degfieldd*).[14] When multiple CIP codes map to a single *degfieldd* code, we take a simple average across the associated CIP-specific skill scores. This yields field-level skill profiles for all non-military-related majors in our data (168 out of 170 majors), based on the skills and tasks required in the occupations that each major prepares its graduates for. We merge these scores into our ACS data, and we also standardize these to have a mean of zero and a unit variance within our analysis sample.

5.2 Skill Cluster Scores across Fields of Study and Occupations

We begin by examining how skill cluster scores vary across fields of study that differ in their potential earnings. Figure 5 documents clear and systematic patterns. Fields of study associated with higher expected earnings tend to equip students with substantially higher levels of Routine and Analytical skills, as well as moderately higher levels of Managerial and Communication skills. In contrast, these higher-earning fields are characterized by lower levels of Physical, Contact, and Social skills.

Figure 6 presents the corresponding skill cluster patterns across occupations with different levels of earnings potential. Higher-paying occupations require substantially higher levels of Analytical, Social, Managerial, and Communication skills, and markedly lower levels of Physical skills, while Contact and Routine skills show little systematic variation across the earnings distribution. The contrast between the skill profiles of high-paying fields of study and those of high-paying occupations—particularly

[14] We use a crosswalk that was sent to us by the IPUMS support team via email.

in Managerial, Social, and Communication skills—suggests that majoring in a high-earning field does not necessarily prepare individuals for entry into the higher-paying occupations.

5.3 Skill Cluster Scores across Race and Ethnicity Groups

We can also compute mean scores across our seven skill clusters for graduates from each race/ethnicity group. Panel A of Table 8 reports mean skill-group scores by race/ethnicity based on individuals' fields of study. Relative to White graduates, the majors that Black individuals graduate from disproportionately prepare them for occupations with high levels of Routine, Social, Contact and Managerial skills, and with low levels of Analytical skills. Hispanics disproportionately graduate from majors that lead to occupations with lower levels of Analytical skills, and higher levels of Social, Contact, Communication, and Managerial skills, although the Hispanic-White gaps in these measures tend to be smaller in magnitude than the Black-White gaps.

Panel B of Table 8 displays the mean skill-group score differences by race and ethnicity based on their occupational employment distributions. Despite graduating from majors that lead to occupations with higher levels of Social and Managerial scores, Black and Hispanic workers tend to work in occupations that are less intensive in these skills, compared to the occupations that White workers are employed in.

We can compute the individual-level difference between the skill cluster scores that they are predicted to have based on their field of study, and the skill cluster scores they actually have based on their occupation. This provides a measure of the extent to which an individual is using more or less of certain skills, relative to what they would be predicted to, based on their field of study. Panel C of Table 8 shows the average of these skill differences for each of our race/ethnicity groups. White workers are employed in occupations that use more Analytical, Social, Communication, and Managerial skills than what their fields of study would predict. On the other hand, Black workers are employed in occupations that use lower levels of *all* skills, compared to what their fields of study would predict. The gaps are particularly large for Social and Managerial skills. Hispanic workers, meanwhile, are employed in occupations with higher levels of Routine and Physical skills than their fields of study would

predict, and lower levels of Social, Communication, and Managerial skills.

Table 9 further explores the dimensions along which the occupational employment distribution of Black and Hispanic workers differs relative to White workers, overall, and conditional on their field of study. The overall differences in the first panel simply reflect the gaps for Black/Hispanic workers relative to White workers shown in Panel B of Table 8. The remaining panels show how these gaps differ according to the earnings potential of their fields of study. Conditional on field of study, Black and Hispanic workers tend to work in occupations that are more intensive in Routine, Physical, and Contact skills, and less intensive in Analytical, Social, Communication and Managerial skills. The contrast is sharper among graduates from high-income majors. This sorting amplifies earnings differences among workers with comparable training.

To more formally document differences in the skill profiles of the occupations that workers end up in, conditional on their detailed field of study, we run a set of regressions of the following form:

$$\text{Skill}_{it}^{o} = \alpha + \text{Race}_i' \, \delta + \lambda_{m(i)} + \text{X}_{it}' \, \gamma + \varepsilon_{it}, \tag{7}$$

where Skill_{it}^{o} is the skill intensity score for the occupation o that individual i works in at time t, Race_i is a vector of indicator variables for individuals who are Black or Hispanic, $\lambda_{m(i)}$ are detailed field of study fixed effects, and X_{it} is a vector of controls for observable demographic and geographic characteristics of individual i at time t. The coefficient of interest, δ, allows us to determine whether there are systematic differences in the skill intensities of the occupations that individuals from minority backgrounds work in, once we control for their detailed field of study, as well as their observable characteristics.[15]

Table 10 presents the results. Panel A begins with a simple specification that does not control for fields of study or for demographic and geographic controls, hence reflecting unconditional differences in occupational sorting by race and ethnicity. The results show that Black and Hispanic workers tend to work in occupations with higher

[15] We control for the same observable characteristics as in our Mincerian log earnings regression, i.e. sex, age and age squared, interaction terms between these variables, indicator variables for marital status, education level, and for reporting two BA degree fields, and a set of fully interacted commuting zone-by-year fixed effects.

Routine, Physical and Contact scores, and lower Analytical, Managerial, Social and Communication scores. Panel B adds detailed field of study fixed effects. Though the racial and ethnic gaps are muted in magnitude, the direction remains the same and the gaps remain highly statistically significant. Hence, the differences in occupational sorting along these skill dimensions are also observed conditional on individuals' detailed fields of study.

Panel C adds controls for the demographic and geographic characteristics of individuals. The patterns remain quite similar. Finally, Panel D adds controls for the scores of all other skill clusters to each regression, hence reflecting differences in the intensity of a particular skill, conditional on the intensity with which all other skills are used in that occupation. Even with this strict specification, we find that Black and Hispanic workers are systematically sorted into jobs with lower Analytical and Managerial intensity, and higher Routine and Contact intensity.

5.4 Field-of-Study–Occupation Matching and Racial Differences in Returns

The relationship between fields of study and occupations can also be investigated through the lens of matching. To explore this, we construct a binary match index M_i that equals one if individual i is employed in an occupation that we classify as matched to their field of study, and zero otherwise.[16] Table 11 reports the share of workers in matched major–occupation pairs by race/ethnicity and across demographic subgroups. Overall, only about one-sixth of workers are employed in occupations that we classify as matched to their detailed field of study, with somewhat lower match rates for Black workers and for younger cohorts.

We then ask whether racial and ethnic differences in the *returns* to working in matched occupations contribute to the residual earnings gaps documented above. In particular, we estimate regressions of the form

$$w_{it} = \alpha + \text{Race}_{it}'\theta + M_{it}\mu + (M_{it} \times \text{Race}_{it})'\kappa + \varepsilon_{it}, \tag{8}$$

[16] We classify a worker as matched ($M_i = 1$) if their observed occupation belongs to the set of potential occupations for their field of study based on the NCES crosswalk discussed above.

where w_{it} denotes residual log earnings for individual i in year t (obtained from a Mincerian log-earnings regression, as described in the data section), Race_{it} is a vector of indicators for Black and Hispanic workers, and M_{it} is the match indicator described above. The coefficient μ captures the return to working in a matched occupation for White workers (the omitted racial group), while the interaction terms $(M_{it} \times \text{Race}_{it})$—with coefficients collected in κ—measure how these returns differ for Black and Hispanic workers relative to Whites.

Table 12 presents estimates of specification (8) for all cohorts combined (Panel A) and separately for older (1955–1974) and younger (1975–1994) birth cohorts (Panels B and C). Across panels, the coefficients on the match indicator in columns (3) and (4) point to a positive but quantitatively modest matching premium: about 0.13 log points in specifications without fixed effects and roughly 0.02–0.03 log points (2–3 percent) once field-of-study and occupation fixed effects are included. In terms of the notation in equation (8), μ measures the average reward to working in a matched occupation for White workers, while the interaction coefficients in κ capture how this premium differs for Black and Hispanic workers relative to Whites. The interaction terms in column (5) show that this premium is smaller for Black workers than for otherwise comparable White workers: The κ coefficient for Black workers is approximately -0.016 log points in the pooled sample and around -0.026 among older cohorts, while it is close to zero and statistically insignificant for younger cohorts. Overall, these results suggest that although working in a matched occupation is associated with higher residual earnings, minority workers—particularly older Black workers—receive somewhat lower rewards than White workers for comparable levels of field–occupation alignment.

5.5 Returns to Skills

The results above help deepen our understanding of the differences in the occupational employment composition of workers from minority backgrounds relative to White workers, conditional on their field of study. As we saw in Table 4, these differences account for 33-38% of the observed racial and ethnic earnings gaps. The remaining 62-67% is driven by differences in earnings among workers with degrees in the same detailed field of study and working in the same detailed occupation. To further

explore these gaps, and following the logic of Manuel & Plesca (2020), we ask whether these earnings gaps reflect differences in the returns to the same "potential skills", as captured by the skills of the occupations that their field of study prepares them for.

We estimate the following regression:

$$w_{it} = \alpha + \text{Race}_i' \, \delta + S_i' \, \beta + (S_i \times \text{Race}_i)' \, \pi + \varepsilon_{it},$$

where w_{it} are residual earnings for individual i observed in year t, and S_i is the vector of "potential skills" of individual i, i.e. the scores for our seven skill clusters based on the occupations that their field of study prepares them for. As above, Race_i is a vector of indicator variables for individuals who are Black or Hispanic. The coefficient β reflect the returns to potential skills for White individuals, while the coefficient π captures the differential return to these skills for Black and Hispanic individuals. Since skills are normalized to be mean zero, the coefficient δ will capture the racial earnings gap for individuals with average potential skills (i.e. with a counterfactual field of study that prepares them for an occupation with average skill demand for all seven skill clusters).

The results are presented in Table 13. Column (1) shows a base regression that only controls for race/ethnicity. This replicates the benchmark residual earnings gaps that we have documented earlier. Column (2) adds controls for potential skills. The results show particularly high returns for analytical skills, and low returns for social skills (conditional on all other skills). Controlling for the skills acquired by individuals through their field of study choices in this way reduces the estimated coefficients on the Black and Hispanic indicator variables only slightly, consistent with our earlier results that field of study choices explain only a small portion of the residual earnings gaps.

Column (3) adds the interaction term between skills and race/ethnicity. The results suggest that the return to potential skills differs systematically across groups. In particular, Managerial skills, which are highly rewarded for White workers, yield smaller returns for Black and Hispanic workers. Contact and Communication skills, which are negatively rewarded for White workers, are positively rewarded for Black and Hispanic workers. Note, however, that controlling for the differential racial and ethnic returns to potential skills does not have a major impact on the baseline coef-

ficients for the Black and Hispanic indicators.

In Column (4) we add occupation fixed effects, in order to control for differences in occupational sorting (conditional on potential skills) and to estimate the differential returns to potential skills *within* occupations. The baseline coefficients for the Black and Hispanic indicators are reduced in absolute value, consistent with the relatively important role for occupational sorting conditional on field of study documented above. However, the findings on the returns to skills to White workers, and the differential returns to Black and Hispanic workers, are fairly consistent with the patterns in Column (3), suggesting that these differences arise within detailed occupations.

Finally, Column (5) controls fully flexibly for the baseline skills acquired by individuals due to their field of study choices, by adding fixed effects for their detailed major. The baseline return to skills for White workers are no longer identified, but the differential returns for Black and Hispanic workers remain very similar to those in Column (4), as do the baseline coefficients on the Black and Hispanic indicators.

6 Conclusions

This paper examines the sizable racial and ethnic earnings gaps that persist among U.S.-born, college-educated, full-time, full-year workers. Using ACS data for 2009–2021, we separate the role of field of study composition and occupational sorting, and consider information on occupational skill and task content from O*NET to provide a rich description of the observed gaps.

We find that differences in field of study composition explain only a modest share of the earnings gap. Occupational sorting is more consequential: around 30-40% of the Black–White and Hispanic–White gap conditional on field of study reflects disproportionate concentration of minorities in lower-paying occupations when compared to White peers majoring in the same field. Yet, a large fraction of the overall earnings gap remains unexplained, i.e., it is observed among workers with degrees in the same detailed field of study who are working in the same detailed occupation.

Using information from O*NET, we show that Black and Hispanic workers tend

to be more concentrated in occupations that require routine and contact tasks, and less concentrated in occupations that involve analytical and managerial tasks, as compared to White worker with degrees in the same field of study. We also explore the extent to which unequal rewards for the same skills can explain the gaps within field of study-occupation cells.

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Table 1: Racial and Ethnic Composition across Various Sample Restrictions

	(1) Age 22-64	(2) +U.S.-born	(3) +BA or above	(4) +FTFY
Fraction White (%)	62.46	73.62	81.40	81.13
Fraction Black (%)	12.11	13.10	7.99	8.27
Fraction Hispanic (%)	16.66	8.97	5.70	5.80
Fraction Other (%)	8.76	4.31	4.92	4.80
Observations	16,490,561	13,870,931	4,705,072	3,142,580

Note: Each column represents a progressively restricted sample. Column (1) includes all individuals aged 22–64; Column (2) further restricts the sample to U.S.-born individuals; Column (3) further restricts the sample to those with a Bachelor's degree or higher; Column (4) further restricts the sample to workers employed full-time, full-year. The data is from the American Community Survey, 2009-2021.

Table 2: Summary Statistics

	(1) Total	(2) White	(3) Black	(4) Hispanic	(5) Other
Average age	41.87	42.40	41.85	38.10	37.60
Within-group fractions (%):					
Female	48.86	47.16	61.77	53.15	50.17
Married	63.03	66.21	45.42	53.67	50.95
Live in Northeast	20.04	21.34	12.97	14.97	16.51
Live in Midwest	23.48	25.91	15.30	9.61	13.24
Live in South	35.59	33.37	62.12	37.11	25.54
Live in West	20.89	19.39	9.62	38.30	44.71
Two BA Fields	11.48	11.80	8.04	10.62	13.06
Graduate Degree	35.78	36.05	36.81	30.63	35.74
Average annual wage earnings	100,649	104,093	77,554	85,022	101,088
% of White average			74.50	81.68	97.11
Observations	3,142,580	2,672,004	175,591	151,556	143,429

Note: The table shows summary statistics for our analysis sample, which includes U.S.-born, full-time, full-year workers aged 22–64 with at least a Bachelor's degree. Average annual wage earnings are in real 2021 dollars. The data are from the American Community Survey, 2009–2021.

Table 3: Residual Earnings Gap Decomposition: Between and Within Fields of Study

		Reference Earnings Group:			
		White		Black/Hispanic	
Earnings Gap	**Total**	**Sorting**	**Within Major**	**Sorting**	**Within Major**
	(1)	(2)	(3)	(4)	(5)
Panel A: All Graduates					
Black–White	-0.154	-0.015	-0.139	-0.022	-0.132
		(9.97%)	(90.03%)	(14.51%)	(85.49%)
Hispanic–White	-0.092	-0.014	-0.079	-0.014	-0.078
		(14.66%)	(85.34%)	(15.00%)	(85.00%)
Panel B: Bachelor's Degree Holders Only					
Black–White	-0.181	-0.020	-0.162	-0.023	-0.158
		(10.90%)	(89.10%)	(12.75%)	(87.25%)
Hispanic–White	-0.102	-0.017	-0.085	-0.017	-0.085
		(16.54%)	(83.46%)	(16.35%)	(83.65%)

Note: The table decomposes the gap in average residual earnings between Black/Hispanic and White workers, indicated in Column (1), into the *sorting* component, reflecting differences in field of study composition, and the *within major* component, reflecting differences in residual earnings by race/ethnicity within fields of study. The analysis is based on 170 detailed field of study categories available in the American Community Survey (ACS) data. Columns (2) and (3) use the formula in Equation (1), which uses average residual earnings of White workers as the reference category; Columns (4) and (5) use the formula in Equation (2), which uses average residual earnings of Black/Hispanic workers as the reference category. The numbers in parenthesis indicate the fraction of the total that each component accounts for. The sample includes U.S.-born, full-time, full-year workers aged 22-64 with at least a Bachelor's degree. Residual earnings are obtained from a regression of log real annual wage and salary income on sex, age and age squared, interaction terms between these variables, indicator variables for marital status, education level, and for reporting two BA degree fields, and a set of fully interacted commuting zone-by-year fixed effects. The data is from the ACS, 2009-2021.

Table 4: Decomposition of Within-Major Residual Earnings Gap: Between and Within Occupations

	Reference Earnings Group:					
	White			Black/Hispanic		
Within-Major Earnings Gap	**Total** (1)	**Sorting** (2)	**Within Occ** (3)	**Total** (4)	**Sorting** (5)	**Within Occ** (6)
Panel A: All Graduates						
Black-White	-0.139	-0.054 (38.47%)	-0.086 (61.53%)	-0.132	-0.054 (40.88%)	-0.078 (59.12%)
Hispanic-White	-0.079	-0.030 (38.61%)	-0.048 (61.39%)	-0.078	-0.035 (44.12%)	-0.044 (55.88%)
Panel B: Bachelor's Degree Holders Only						
Black-White	-0.162	-0.067 (41.61%)	-0.094 (58.39%)	-0.158	-0.071 (44.57%)	-0.088 (55.43%)
Hispanic-White	-0.085	-0.035 (41.69%)	-0.049 (58.31%)	-0.085	-0.043 (50.24%)	-0.042 (49.76%)

Note: The table decomposes the within-field-of-study gap in average residual earnings between Black/Hispanic and White workers, indicated in Column (1) and (4), into the *sorting* component, reflecting differences in occupational composition (conditional on field of study), and the *within occupation* component, reflecting differences in residual earnings by race/ethnicity within occupations (conditional on field of study). The analysis is based on 170 detailed field of study categories and 479 occupation categories available in the American Community Survey (ACS) data. Columns (2) and (3) use the formula in Equation (5), which uses average residual earnings of White workers as the reference category; Columns (5) and (6) use the formula in Equation (6), which uses average residual earnings of Black/Hispanic workers as the reference category. The numbers in parenthesis indicate the fraction of the total that each component accounts for. The sample includes U.S.-born, full-time, full-year workers aged 22-64 with at least a Bachelor's degree. Residual earnings are obtained from a regression of log real annual wage and salary income on sex, age and age squared, interaction terms between these variables, indicator variables for marital status, education level, and for reporting two BA degree fields, and a set of fully interacted commuting zone-by-year fixed effects. The data is from the ACS, 2009-2021.

Table 5: Differences in Occupational Sorting Conditional on Field of Study

Major Category	**Sorting Gap**	**Occupational Income Category**			
		High	Med-High	Med-Low	Low
High	Black–White	-11.26	-0.84	4.06	8.04
	Hispanic–White	-5.21	-0.75	1.78	4.18
Medium-High	Black–White	-10.41	-3.70	2.64	11.47
	Hispanic–White	-5.65	-1.71	1.72	5.65
Medium-Low	Black–White	-6.48	-1.38	-3.07	10.94
	Hispanic–White	-4.80	-1.96	-2.18	8.94
Low	Black–White	-3.09	-0.88	-2.16	6.13
	Hispanic–White	-2.30	-1.16	-1.19	4.65

Note: Each cell indicates the percentage point difference between the share of Black/Hispanic individuals from a given field of study group that are employed in a given occupational income group, and the corresponding share for White individuals. The sample includes U.S.-born, full-time, full-year workers aged 22-64 with at least a Bachelor's degree. Detailed field of study and occupational codes are grouped into four quartiles based on their earnings potential. The earnings potential of each detailed field of study (each detailed occupation) is proxied by the median earnings of White males aged 43 to 57 with a degree in that field (working in that occupation). The data is from the American Community Survey, 2009-2021.

Table 6: Residual Earnings Gaps within Field of Study-Occupation Cells

Major Category	**Residual Gap**	**Occupational Income Category**			
		High	Med-High	Med-Low	Low
High	Black–White	-0.160	-0.153	-0.059	-0.052
	Hispanic–White	-0.096	-0.098	-0.063	-0.024
Medium-High	Black–White	-0.199	-0.169	-0.101	-0.072
	Hispanic–White	-0.138	-0.105	-0.045	-0.005
Medium-Low	Black–White	-0.170	-0.128	-0.024	-0.016
	Hispanic–White	-0.113	-0.088	-0.020	0.009
Low	Black–White	-0.138	-0.123	-0.034	-0.044
	Hispanic–White	-0.119	-0.079	-0.015	0.001

Note: Each cell indicates the difference in mean residual earnings between Black/Hispanic workers and White workers from a given field of study group that are employed in a given occupational income group. The sample includes U.S.-born, full-time, full-year workers aged 22-64 with at least a Bachelor's degree. Residual earnings are obtained from a regression of log real annual wage and salary income on sex, age and age squared, interaction terms between these variables, indicator variables for marital status, education level, and for reporting two BA degree fields, and a set of fully interacted commuting zone-by-year fixed effects. Detailed field of study and occupational codes are grouped into four quartiles based on their earnings potential. The earnings potential of each detailed field of study (each detailed occupation) is proxied by the median earnings of White males aged 43 to 57 with a degree in that field (working in that occupation). The data is from the American Community Survey, 2009-2021.

Table 7: Mapping of O*NET Elements to Skill Clusters

Cluster	O*NET Element	Module
Routine	Degree of Automation	Work Context
	Importance of Repeating Same Tasks	Work Context
Analytical	Mathematical Reasoning	Abilities
	Using Mathematics to Solve Problems	Skills
	Knowledge of Mathematics	Knowledge
Social	Social Perceptiveness	Skills
	Negotiation	Skills
	Persuasion	Skills
	Coordination	Skills
Physical	Multilimb Coordination	Abilities
	Gross Body Coordination	Abilities
Contact	Contact With Others	Work Context
	Deal With External Customers or the Public in General	Work Context
Communication	Written Expression	Abilities
	Oral Expression	Abilities
	Speaking	Skills
	Written Comprehension	Abilities
	Reading Comprehension	Skills
	Face-to-Face Discussions	Work Context
Managerial	Judgment and Decision Making	Skills
	Making Decisions and Solving Problems	Work Activities
	Judging the Qualities of Things, Services, or People	Work Activities
	Freedom to Make Decisions	Work Context
	Coordinate or Lead Others	Work Context
	Impact of Decisions on Co-workers or Company Results	Work Context
	Guiding, Directing, and Motivating Subordinates	Work Activities
	Administration and Management	Knowledge
	Management of Financial Resources	Skills
	Management of Material Resources	Skills
	Management of Personnel Resources	Skills

Note: The table indicates the O*NET elements that we include in each of the seven clusters that we use to characterize occupations. The final column indicated the O*NET module that each particular element is drawn from. We use data from O*NET 20.1.

Table 8: Skill Cluster Scores by Race/Ethnicity

Panel A: Based on Field of Study Composition

	Routine	Analytical	Social	Physical	Contact	Communic	Managerial
White	-0.0083	0.0092	-0.0212	-0.0000	-0.0031	-0.0043	-0.0170
Black	0.0759	-0.1217	0.2239	0.0581	0.1285	-0.0294	0.1248
Hispanic	-0.0189	-0.0886	0.0596	0.0183	0.0366	0.0249	0.0268

Panel B: Based on Occupational Employment Composition

	Routine	Analytical	Social	Physical	Contact	Communic	Managerial
White	-0.0126	0.0256	0.0122	-0.0068	-0.0068	0.0152	0.0229
Black	0.0712	-0.2206	-0.0388	0.0659	0.0975	-0.1098	-0.1384
Hispanic	0.0072	-0.1041	-0.0319	0.0434	0.0641	-0.0540	-0.0973

Panel C: Occupation vs Field of Study Score

	Routine	Analytical	Social	Physical	Contact	Communic	Managerial
White	-0.0043 ***	0.0164 ***	0.0333 ***	-0.0067 ***	-0.0037 ***	0.0195 ***	0.0399 ***
Black	-0.0047 *	-0.0989 ***	-0.2627 ***	0.0078 ***	-0.0310 ***	-0.0804 ***	-0.2632 ***
Hispanic	0.0261 ***	-0.0155 ***	-0.0915 ***	0.0251 ***	0.0274 ***	-0.0788 ***	-0.1241 ***

Note: Panel A reports mean skill cluster scores by race/ethnicity based on individuals' fields of study. Panel B reports mean skill cluster scores by race/ethnicity based on the occupations that individuals are employed in. Panel C reports the average difference between the occupation-based skill cluster score and the field of study-based score. It can be interpreted as a measure of the extent to which individuals from a particular group use more or less of a particular skill, relative to what would be predicted based on their field of study. Stars indicate the statistical significance of this difference: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Details on the assignment of skill cluster scores from O*NET to fields of study and occupations are provided in Section 5.1. The data is from O*NET 20.1 and the American Community Survey, 2009–2021.

Table 9: Differences in Skill Cluster Scores based on Occupational Employment Composition, according to Field of Study Earnings Potential Groups

Major	**Skill**	**Skill Cluster**						
Category	**Gap**	Routine	Analytical	Social	Physical	Contact	Communic	Managerial
Overall	Black-White	0.08	-0.25	-0.05	0.07	0.10	-0.12	-0.16
	Hispanic-White	0.02	-0.13	-0.04	0.05	0.07	-0.07	-0.12
High	Black-White	0.16	-0.23	-0.10	0.07	0.12	-0.17	-0.18
	Hispanic-White	0.05	-0.07	-0.09	0.05	0.02	-0.11	-0.13
Med-High	Black-White	0.12	-0.23	-0.19	0.05	0.05	-0.15	-0.23
	Hispanic-White	0.04	-0.10	-0.09	0.03	0.04	-0.05	-0.12
Med-Low	Black-White	0.08	-0.19	-0.05	0.07	0.07	-0.14	-0.14
	Hispanic-White	0.03	-0.14	-0.06	0.06	0.08	-0.10	-0.14
Low	Black-White	0.05	-0.18	0.06	0.04	0.07	-0.01	-0.07
	Hispanic-White	-0.00	-0.08	-0.00	0.01	0.05	-0.01	-0.08

Note: The table shows the average difference in the skill cluster scores across race/ethnicity groups based on the occupations that they are employed in, overall and conditional on their field of study. The assignment of skill cluster scores from O*NET to occupations is discussed in Section 5.1. Detailed fields of study are grouped into four earnings-potential categories based on the median earnings of White males aged 43 to 57 with a degree in that field. The data is from O*NET 20.1 and the American Community Survey, 2009–2021.

Table 10: Regression of Occupation-Level Skill Scores on Race/Ethnicity Dummies

Panel A: No Controls							
	Routine	Analytical	Social	Physical	Contact	Communic	Managerial
Black	0.0839***	-0.2462***	-0.0510***	0.0727***	0.1043***	-0.1250***	-0.1613***
	(0.0032)	(0.0032)	(0.0033)	(0.0032)	(0.0029)	(0.0033)	(0.0032)
Hispanic	0.0199***	-0.1298***	-0.0441***	0.0502***	0.0709***	-0.0692***	-0.1202***
	(0.0033)	(0.0034)	(0.0034)	(0.0034)	(0.0033)	(0.0033)	(0.0033)
Panel B: Add Field of Study Fixed Effects							
	Routine	Analytical	Social	Physical	Contact	Communic	Managerial
Black	0.0484***	-0.1526***	-0.0896***	0.0546***	0.0484***	-0.1009***	-0.1437***
	(0.0030)	(0.0029)	(0.0032)	(0.0031)	(0.0028)	(0.0032)	(0.0032)
Hispanic	0.0108***	-0.0660***	-0.0657***	0.0355***	0.0410***	-0.0562***	-0.1076***
	(0.0031)	(0.0031)	(0.0032)	(0.0032)	(0.0030)	(0.0032)	(0.0033)
Panel C: Add Demographic and Geographic Controls							
	Routine	Analytical	Social	Physical	Contact	Communic	Managerial
Black	0.0402***	-0.1614***	-0.0726***	0.0941***	0.0518***	-0.1023***	-0.1213***
	(0.0031)	(0.0030)	(0.0033)	(0.0031)	(0.0029)	(0.0031)	(0.0032)
Hispanic	0.0210***	-0.0701***	-0.0435***	0.0289***	0.0306***	-0.0316***	-0.0680***
	(0.0032)	(0.0033)	(0.0034)	(0.0034)	(0.0033)	(0.0033)	(0.0034)
Panel D: Add Controls for all Other Occupation-Level Skill Cluster Scores							
	Routine	Analytical	Social	Physical	Contact	Communic	Managerial
Black	0.0429***	-0.0714***	-0.0061***	0.0204***	0.0127***	0.0051***	-0.0118***
	(0.0027)	(0.0021)	(0.0014)	(0.0022)	(0.0023)	(0.0017)	(0.0016)
Hispanic	0.0170***	-0.0319***	-0.0107***	0.0071***	0.0179***	0.0167***	-0.0096***
	(0.0029)	(0.0023)	(0.0015)	(0.0024)	(0.0025)	(0.0019)	(0.0017)

Note: Each panel reports coefficients from separate regressions of the indicated occupation-based skill cluster score on race/ethnicity indicators. The assignment of skill cluster scores from O*NET to occupations is discussed in Section 5.1. The control variables included in Panel C are: sex, age and age squared, interaction terms between these variables, indicator variables for marital status, education level, and reporting two BA degree fields, as well as fully interacted commuting-zone-by-year fixed effects. Panel D additionally controls for all other skill cluster scores based on the individual's occupation. The data is from O*NET 20.1 and the American Community Survey, 2009–2021. The total number of observations across all regressions is 3,125,697 Robust standard errors are in parentheses. *, **, *** denote significance at the 10, 5, and 1 percent levels, respectively.

Table 11: Summary of Shares of Workers in Matched Major–Occupation Pairs

	(1) Overall	(2) White	(3) Black	(4) Hispanic	(5) Other
All workers	16.3	16.6	14.3	15.2	16.1
Women	15.9	16.2	14.7	14.2	15.4
Men	16.7	16.9	13.7	16.5	16.9
Northeast	15.8	16.0	13.2	15.0	16.8
Midwest	17.2	17.4	14.2	17.2	15.6
South	16.5	16.9	14.7	15.9	16.2
West	15.4	15.6	13.5	14.2	16.0
Cohort 1955–1974	16.9	17.2	15.1	16.3	15.3
Cohort 1975–1994	15.9	16.3	13.7	14.9	16.0

Note: The table reports the share of workers whose detailed occupation is classified as "matched" to their detailed field of study, by race/ethnicity and demographic and geographic subgroups. Values are in percent.

Table 12: Residual Earnings Regressions with Major–Occupation Match

	(1)	(2)	(3)	(4)	(5)
Panel A: All cohorts					
Black	-0.155***	-0.139***	-0.135***	-0.091***	-0.088***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)
Hispanic	-0.092***	-0.079***	-0.078***	-0.049***	-0.049***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Match			0.133***	0.024***	0.026***
			(0.001)	(0.001)	(0.001)
Black × Match					-0.016***
					(0.004)
Hispanic × Match					-0.002
					(0.004)
Observations	3,125,697	3,125,697	3,125,697	3,125,697	3,125,697
R^2	0.00724	0.09120	0.09635	0.22960	0.22961
Panel B: Older cohorts (1955–1974)					
Black	-0.179***	-0.156***	-0.152***	-0.097***	-0.092***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Hispanic	-0.089***	-0.073***	-0.072***	-0.046***	-0.046***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Match			0.132***	0.019***	0.021***
			(0.002)	(0.002)	(0.002)
Black × Match					-0.026***
					(0.006)
Hispanic × Match					-0.003
					(0.007)
Observations	1,174,087	1,174,087	1,174,087	1,174,087	1,174,087
R^2	0.00785	0.08500	0.08969	0.24830	0.24832
Panel C: Younger cohorts (1975–1994)					
Black	-0.135***	-0.127***	-0.122***	-0.088***	-0.088***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Hispanic	-0.094***	-0.084***	-0.083***	-0.063***	-0.063***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Match			0.129***	0.025***	0.025***
			(0.002)	(0.002)	(0.002)
Black × Match					-0.004
					(0.006)
Hispanic × Match					0.002
					(0.005)
Observations	1,227,302	1,227,302	1,227,302	1,227,302	1,227,302
R^2	0.00770	0.11302	0.11852	0.23390	0.23390
Major FE	No	Yes	Yes	Yes	Yes
Occupation FE	No	No	No	Yes	Yes

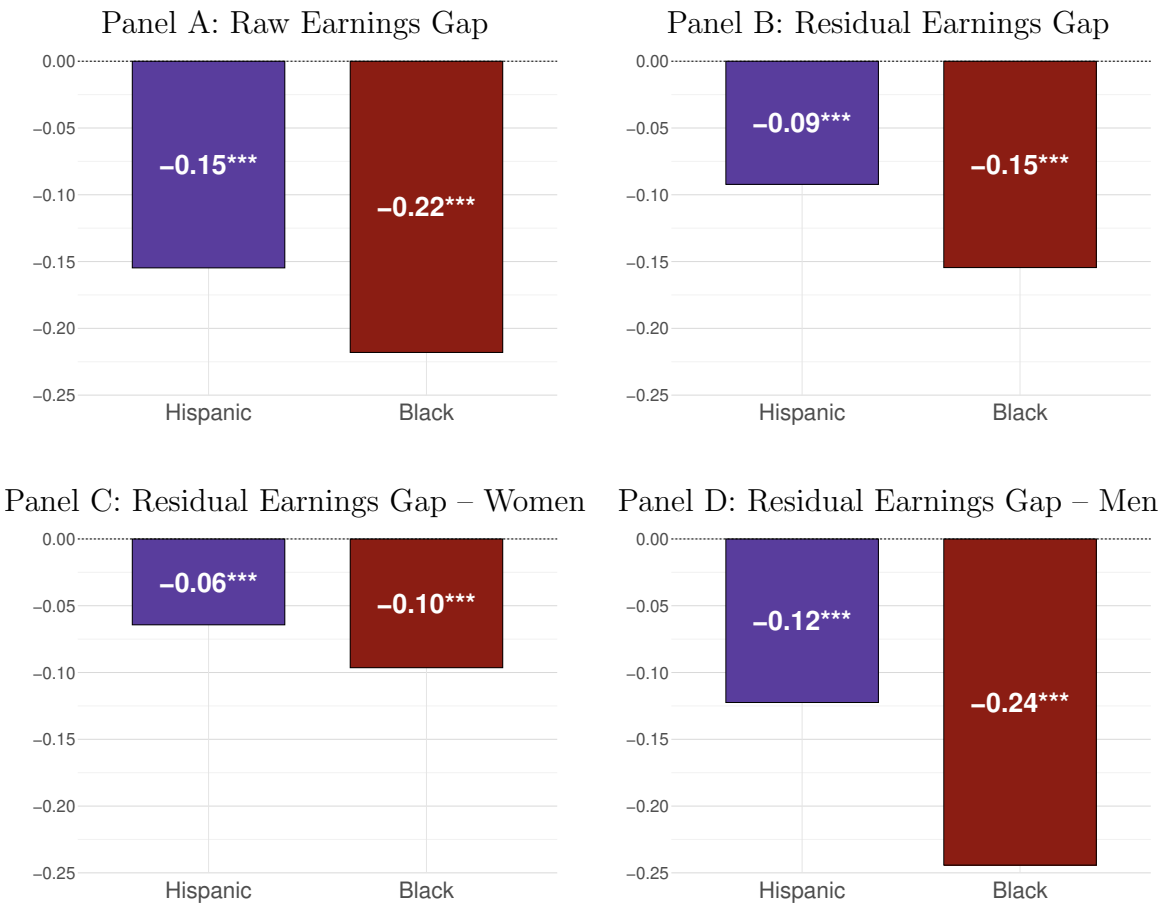
Note: The table reports results from regressions where the dependent variable is residual log earnings. Residual earnings are obtained from a Mincerian regression of log real annual earnings on sex, age and age squared, interactions between these variables, indicators for marital status, education level, and reporting two BA degree fields, as well as fully interacted commuting-zone-by-year fixed effects. The key regressors in this table are race indicators, a major–occupation match indicator, their interactions, and detailed field-of-study and occupation fixed effects, as indicated in the table. The data come from the American Community Survey, 2009–2021. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 13: Residual Earnings Regressions with Skills

	(1)	(2)	(3)	(4)	(5)
Black	-0.15501***	-0.14626***	-0.14174***	-0.08883***	-0.08800***
	(0.00153)	(0.00152)	(0.00158)	(0.00147)	(0.00147)
Hispanic	-0.09231***	-0.08226***	-0.08275***	-0.05025***	-0.05002***
	(0.00169)	(0.00166)	(0.00167)	(0.00154)	(0.00153)
Routine		0.05598***	0.05907***	0.02127***	(omitted)
		(0.00045)	(0.00048)	(0.00052)	
Analytical		0.09409***	0.09286***	0.06718***	(omitted)
		(0.00052)	(0.00055)	(0.00055)	
Social		-0.01308***	-0.01387***	-0.00408***	(omitted)
		(0.00077)	(0.00082)	(0.00082)	
Physical		0.01597***	0.01230***	0.00418***	(omitted)
		(0.00043)	(0.00045)	(0.00051)	
Contact		0.00051	-0.00124**	0.01982***	(omitted)
		(0.00049)	(0.00052)	(0.00052)	
Communication		0.00414***	-0.00032	-0.00486***	(omitted)
		(0.00050)	(0.00053)	(0.00056)	
Managerial		0.00824***	0.01419***	-0.01101***	(omitted)
		(0.00080)	(0.00085)	(0.00084)	
Black × Routine			-0.02395***	-0.01600***	-0.01693***
			(0.00187)	(0.00174)	(0.00175)
Black × Analytical			0.00593**	-0.00166	0.00217
			(0.00237)	(0.00222)	(0.00222)
Black × Social			0.00342	0.00486*	0.00368
			(0.00304)	(0.00285)	(0.00285)
Black × Physical			0.02675***	0.01961***	0.02110***
			(0.00181)	(0.00166)	(0.00165)
Black × Contact			0.00922***	-0.00029	0.00184
			(0.00224)	(0.00208)	(0.00208)
Black × Communication			0.03828***	0.02786***	0.02861***
			(0.00217)	(0.00200)	(0.00201)
Black × Managerial			-0.04090***	-0.02600***	-0.02566***
			(0.00312)	(0.00292)	(0.00293)
Hispanic × Routine			-0.01988***	-0.01614***	-0.01421***
			(0.00208)	(0.00192)	(0.00191)
Hispanic × Analytical			0.00485**	-0.00007	0.00089
			(0.00242)	(0.00221)	(0.00220)
Hispanic × Social			-0.00433	0.00352	0.00730**
			(0.00332)	(0.00305)	(0.00305)
Hispanic × Physical			0.01259***	0.01113***	0.01421***
			(0.00202)	(0.00187)	(0.00185)
Hispanic × Contact			0.01986***	0.00956***	0.00699***
			(0.00219)	(0.00201)	(0.00201)
Hispanic × Communication			0.01351***	0.01336***	0.01440***
			(0.00228)	(0.00212)	(0.00211)
Hispanic × Managerial			-0.01907***	-0.01825***	-0.02067***
			(0.00354)	(0.00328)	(0.00327)
Occupation FE	No	No	No	Yes	Yes
Major FE	No	No	No	No	Yes
R^2	0.0072	0.0568	0.0578	0.2221	0.2300
N (unweighted)			3,125,697		

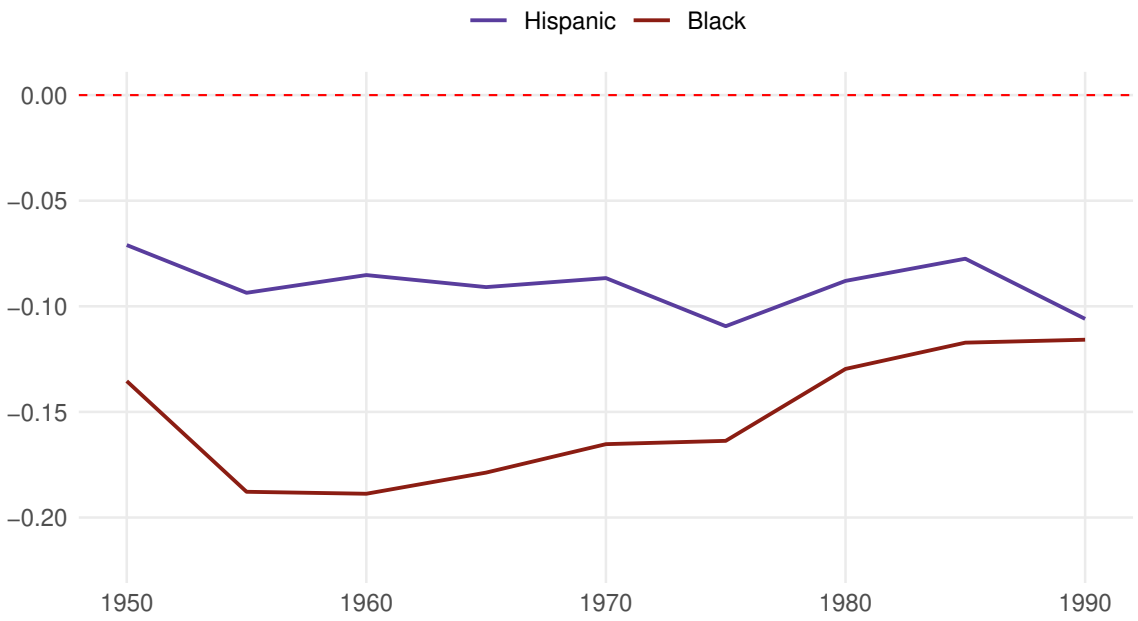
Note: The table shows results for a set of regressions that use residual earnings as the dependent variable. Residual earnings are obtained from a Mincerian regression of log real annual earnings on sex, age and age squared, interaction terms between these variables, indicator variables for marital status, education level, and reporting two BA degree fields, as well as fully interacted commuting-zone-by-year fixed effects. The control variables are skill cluster scores based on individuals' field of study, assigned as discussed in Section 5.1. The data are from O*NET 20.1 and the American Community Survey, 2009–2021. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure 1: Earnings Gaps relative to White Workers



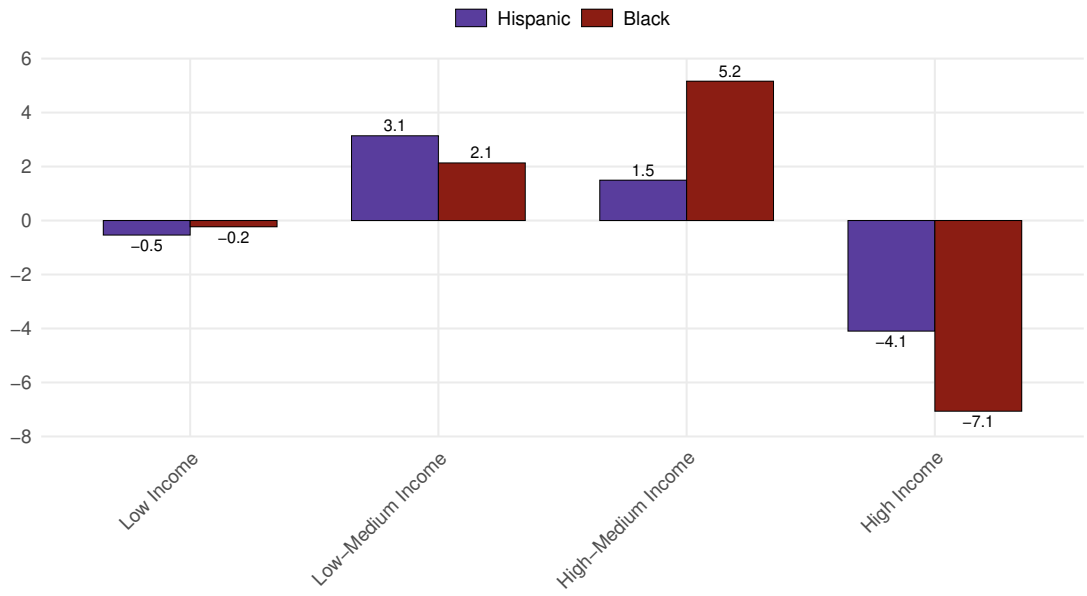
Note: The figure plots the earnings differential for Black and Hispanic workers relative to White workers. The sample includes U.S.-born, full-time, full-year workers aged 22-64 with at least a Bachelor's degree. Panel A computes differences in raw log real average annual wage earnings. Panels B, C, and D compute differences in residual earnings. The residuals are obtained from a regression of log real earnings on sex, age and age squared, interaction terms between these variables, indicator variables for marital status, education level, and for reporting two BA degree fields, and a set of fully interacted commuting zone-by-year fixed effects. The data is from the American Community Survey, 2009-2021.

Figure 2: Residual Earning Gaps across Birth Cohorts



Note: The figure plots the difference in average residual earnings for Black and Hispanic workers relative to White workers, for individuals from different birth cohorts. The sample includes U.S.-born, full-time, full-year workers aged 22-64 with at least a Bachelor's degree. Residual earnings are obtained from a regression of log real earnings on sex, age and age squared, interaction terms between these variables, indicator variables for marital status, education level, and for reporting two BA degree fields, and a set of fully interacted commuting zone-by-year fixed effects. The data is from the American Community Survey, 2009-2021.

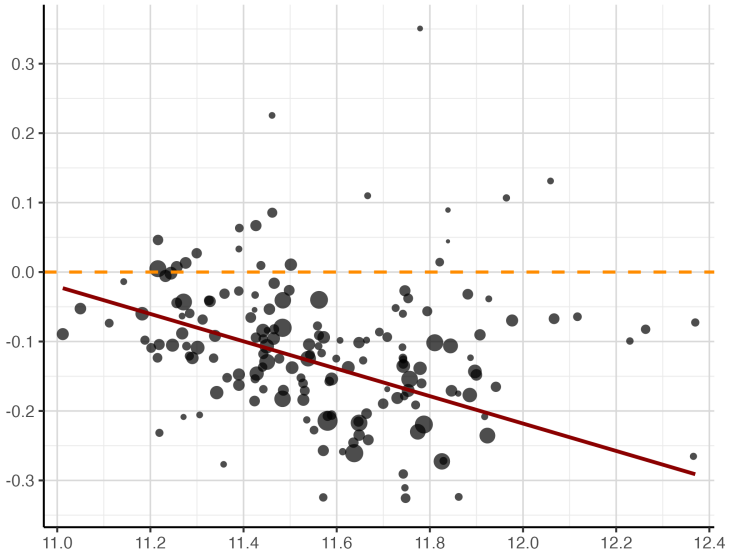
Figure 3: Sorting Differences across Fields of Study



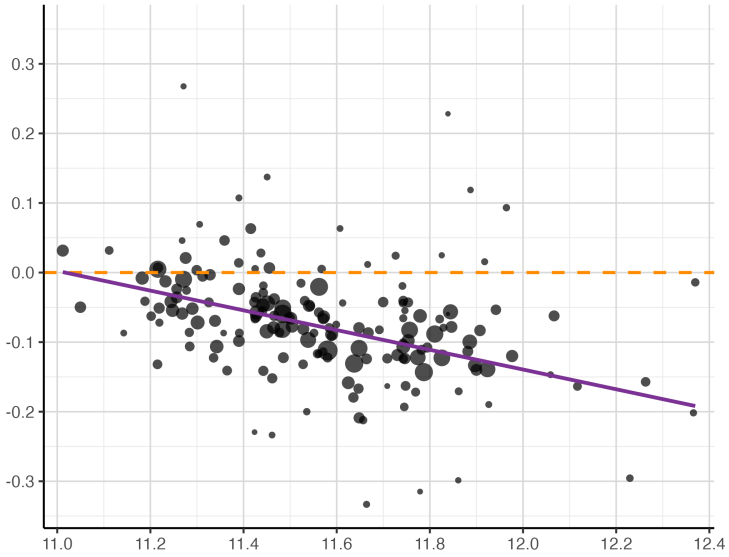
Note: The figure plots the percentage point difference in the fraction of Black and Hispanic workers with degrees in fields of study with different earnings potentials, relative to White workers. The earnings potential of each detailed field of study is proxied by the median earnings of White males aged 43 to 57 with a degree in that field. Fields of study are then grouped into four employment-weighted quartiles (from low income to high income). See Appendix Table A.1 for the detailed mapping. The data is from the American Community Survey, 2009-2021.

Figure 4: Residual Earnings Gaps within Fields of Study

Panel A: Black–White

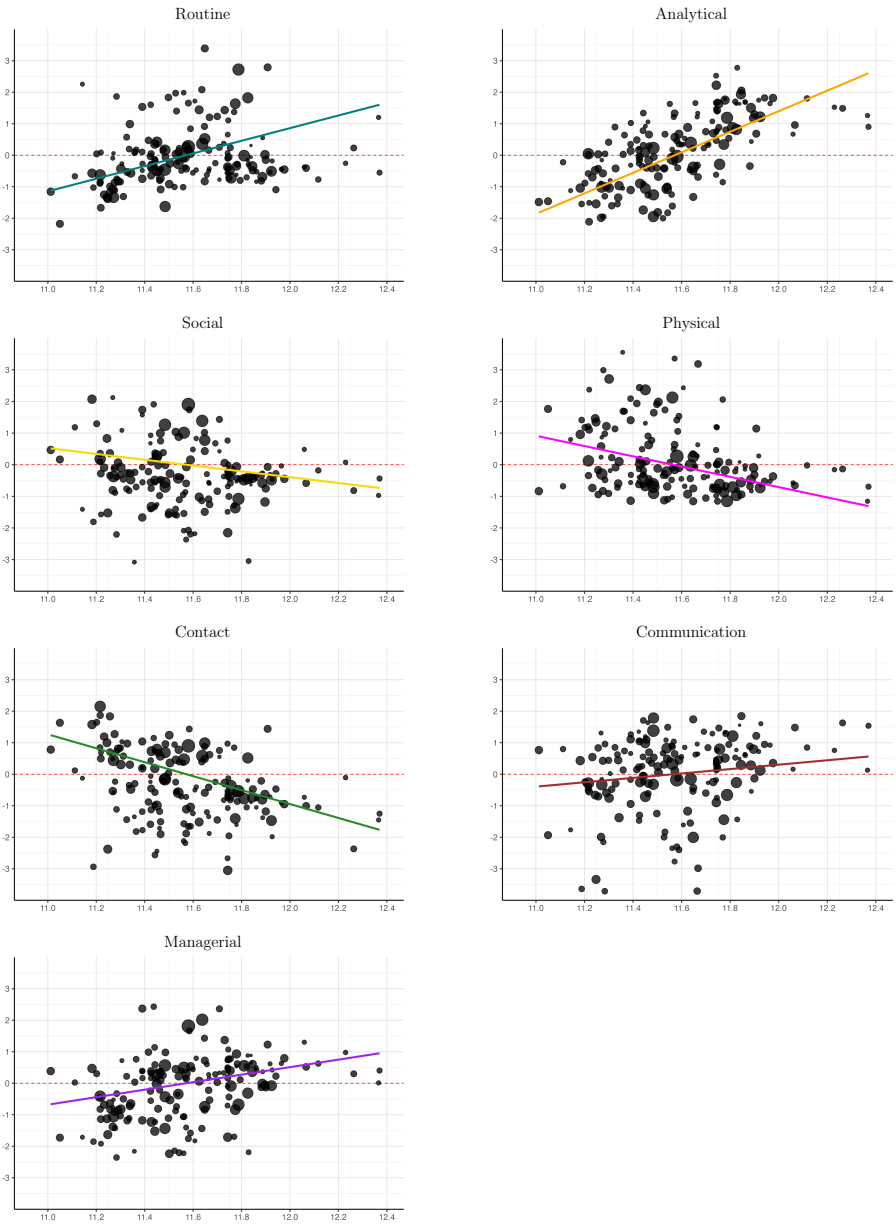


Panel B: Hispanic–White



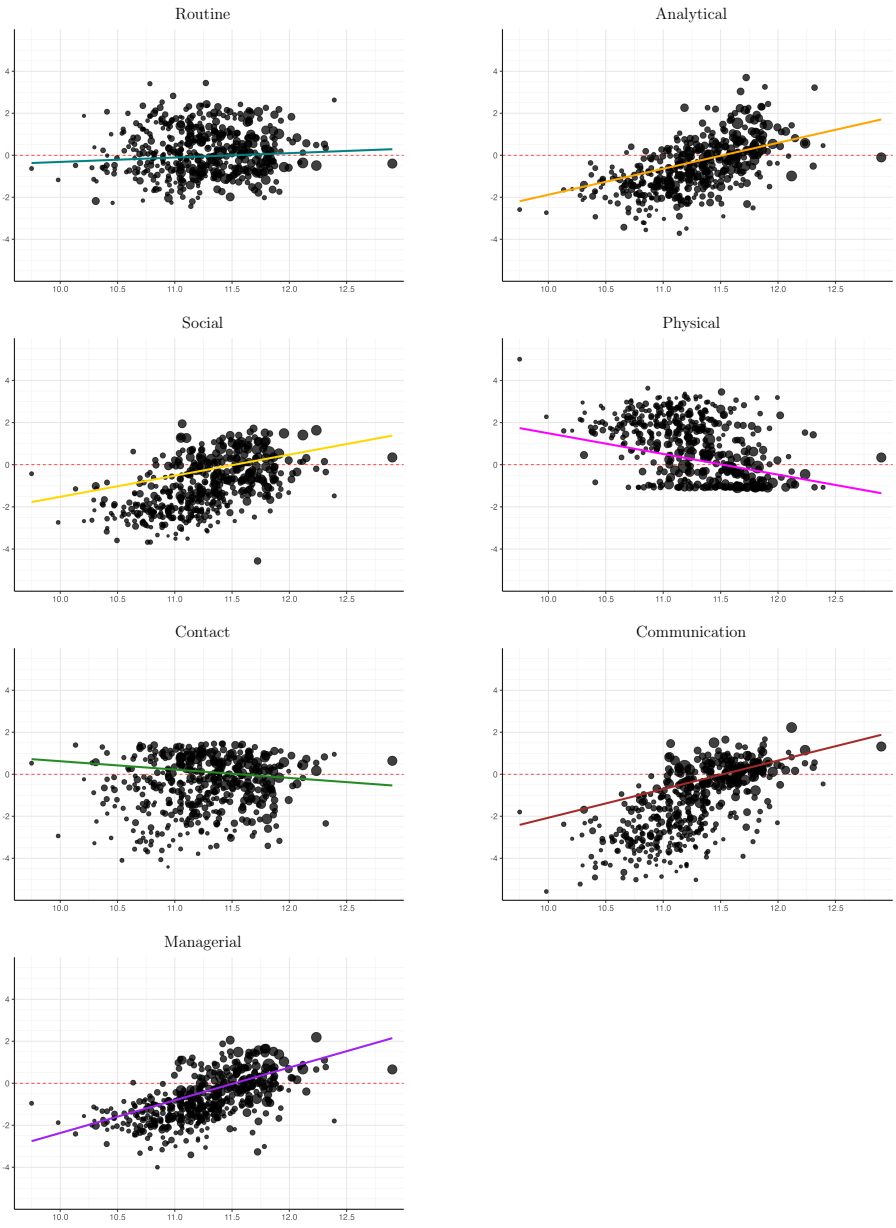
Note: Each dot represents a field of study. The vertical axis plots the difference in mean residual earnings between Black and White workers (Panel A) or between Hispanic and White workers (Panel B), while the horizontal axis plots the log of potential earnings for each field of study. Residual earnings are obtained from a regression of log real annual earnings on sex, age and age squared, interaction terms between these variables, indicator variables for marital status, education level, and reporting two BA degree fields, as well as fully interacted commuting-zone-by-year fixed effects. The sample consists of U.S.-born, full-time, full-year workers aged 22–64 with at least a Bachelor's degree, drawn from the ACS 2009–2021.

Figure 5: Skill Intensity across Fields of Study



Note: Each panel plots, at the field-of-study level, log potential wages (horizontal axis) against the average intensity of one of the seven O*NET skill clusters (vertical axis). Points represent fields of study, with dot sizes proportional to their total ACS sample weight. The solid line shows a weighted linear regression of each skill measure on log potential wage. Together, the seven panels illustrate how potential earnings across fields of study relate to average levels of Routine, Analytical, Social, Physical, Contact, Communication, and Managerial skills.

Figure 6: Skill Intensity across Occupations



Note: Each panel plots, at the occupation level, log potential wages (horizontal axis) against the average intensity of one of the seven O*NET skill clusters (vertical axis). Points represent occupations, with dot sizes proportional to their total ACS sample weight. The solid line shows a weighted linear regression of each skill measure on log potential wage. Together, the seven panels illustrate how potential earnings across occupations relate to average levels of Routine, Analytical, Social, Physical, Contact, Communication, and Managerial skills.

Appendix A Appendix Tables

Table A.1: Earnings potential of detailed fields of study

Major	Earnings potential	Income group	Major	Earnings potential	Income group
Theology/Relig	60,592	Low	Early Child Ed	62,928	Low
Couns Psych	66,941	Low	Library Sci	69,063	Low
Social Work	71,855	Low	Studio Arts	72,278	Low
Human Serv/Comm	73,255	Low	Misc Health Med	74,255	Low
Elem Ed	74,311	Low	Teacher Ed–Mult	74,336	Low
Drama/Theatre	74,520	Low	Cosmet/Culinary	74,560	Low
Precision/Ind Arts	75,513	Low	Art & Music Ed	75,537	Low
Special Needs Ed	76,430	Low	Fine Arts	76,689	Low
Soc/Hist Teach Ed	77,382	Low	Secondary Teach	77,382	Low
School Stud Couns	78,288	Low	Music	78,301	Low
General Ed	78,524	Low	Misc Agriculture	78,524	Low
Lang & Drama Ed	78,884	Low	Vis/Perf Arts	79,031	Low
Comm Tech	79,506	Low	Sci/Comp Teach Ed	79,572	Low
Phys/Health Teach	80,028	Low	Math Teach Ed	80,773	Low
Phys Fit/Recreation	80,933	Low	Misc Fine Arts	81,289	Low
Film/Video/Photo	81,806	Low	General Agric	82,909	Low
Composition/Speech	83,758	Low	Mass Media	84,015	Low
Comm Art/Graphic	84,323	Low	Elec/Mech Repairs	85,744	Low
Nat Res Mgmt	85,744	Low	Plant Sci/Agron	86,226	Low
Forestry	88,413	Low	Hospitality Mgmt	88,437	Low
Clinical Psych	88,437	Low	Philosophy/Relig	88,437	Low
Misc Biology	88,516	Low	Animal Sci	90,714	Low
Geography	91,460	Low	Social Psych	91,460	Low
Educational Psych	91,569	Low	Comp Net/Telecom	91,569	Low
Anthro/Archaeol	91,724	Low	Agric Prod/Mgmt	91,724	Low
Liberal Arts	91,874	Low	Educ Admin/Superv	92,713	Low
Interdisc Soc Sci	93,054	Low	Journalism	93,133	Low
Ecology	93,181	Low	Gen Social Sci	93,200	Low
Humanities	93,200	Low	Sociology	93,882	Low
Soil Sci	93,962	Low-med	Crim Justice/Fire	93,964	Low-med
Comm Disord Sci	94,417	Low-med	Botany	94,961	Low-med
Art Hist/Crit	95,002	Low-med	Family/Cons Sci	95,275	Low-med
Criminology	95,380	Low-med	Environ Sci	95,391	Low-med
Community/Public Hlth	96,451	Low-med	Psychology	97,119	Low-med
Communications	97,119	Low-med	English Lang/Lit	97,176	Low-med
Gen Med/Health Serv	97,292	Low-med	Med Tech/Techs	98,517	Low-med
Fr/Ger/Latn/Other FL	98,870	Low-med	Treatment Therapy	99,138	Low-med
Other Foreign Lang	101,044	Low-med	Comp Info Mgmt/Sec	101,498	Low-med
HR/Personnel Mgmt	101,557	Low-med	Ind Prod Tech	101,870	Low-med
U.S. History	102,307	Low-med	History (Other)	102,604	Low-med
Advert/PR	102,807	Low-med	Pre-Law/Legal Std	103,015	Low-med

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Major	Earnings potential	Income group	Major	Earnings potential	Income group
Engineering Tech	103,913	Low-med	Linguistics/Comp Lit	104,686	Low-med
Comp Prog/Data Proc	104,930	Low-med	Intercult/Intl Std	105,019	Low-med
Nursing	105,039	Low-med	Agric Economics	105,626	Low-med
Mech Eng Related Tech	105,990	Low-med	Geology/Earth Sci	106,008	Low-med
Architecture	106,096	High-Med	Bus Mgmt/Admin	106,977	High-Med
Misc Eng Tech	106,977	High-Med	Public Admin	107,359	High-Med
Multi/Gen Science	107,910	High-Med	Elec Eng Tech	107,910	High-Med
Misc Social Sci	108,989	High-Med	Military Tech	109,440	High-Med
Nuclear/Bio Tech	109,882	High-Med	Ind/Org Psych	110,502	High-Med
Comp & Info Systems	111,840	High-Med	Misc Bus/Med Admin	113,082	High-Med
General Business	113,270	High-Med	Ops/Log/E-Comm	114,325	High-Med
Area/Ethnic/Civiliz	114,441	High-Med	Marketing/Res	114,461	High-Med
Health/Med Admin Serv	114,481	High-Med	Biological Eng	115,468	High-Med
Construction Serv	116,318	High-Med	Geosciences	116,318	High-Med
Oceanography	116,589	High-Med	Transport Sci/Tech	116,750	High-Med
Misc Psychology	119,562	High-Med	Information Sci	120,538	High-Med
Intl Business	121,600	High-Med	Physical Sci	121,600	High-Med
Atmos Sci/Meteorol	123,811	High-Med	MIS/Statistics	124,266	High-Med
Environ Engineering	125,638	High-Med	Public Policy	125,758	High-Med
Statistics/Decision	125,758	High-Med	Nutrition Sci	125,855	High-Med
Mathematics	125,855	High-Med	Misc Engineering	125,855	High-Med
Food Science	125,855	High-Med	Eng/Ind Mgmt	126,128	High-Med
Ind/Manuf Eng	126,305	High-Med	Architectural Eng	126,305	High-Med
Business Econ	126,487	High-Med	Physiology	127,188	High-Med
General Engineering	127,188	High-Med	Pol Sci/Govt	127,578	High-Med
Med Assisting Serv	129,237	High	Computer Science	129,836	High
Astronomy/Astrophys	130,480	High	Civil Engineering	130,480	High
Microbiology	130,889	High	Accounting	131,550	High
Zoology	132,510	High	Biology	134,665	High
Materials Eng/Mat Sci	136,092	High	Mining/Mineral Eng	136,693	High
Finance	136,727	High	Applied Math	137,190	High
Pharmacology	138,533	High	Geol/Geophys Eng	138,533	High
Mechanical Eng	139,288	High	Physics	139,581	High
Metallurgical Eng	141,626	High	Eng Mech/Phys/Sci	141,763	High
International Rel	144,557	High	Electrical Eng	145,166	High
Math & Comp Sci	145,397	High	Chemistry	146,771	High
Computer Eng	147,251	High	Pharmacy/Admin	148,386	High
Naval Arch/Marine Eng	149,887	High	Economics	150,765	High
Genetics	151,213	High	Aerospace Eng	153,543	High
Nuclear Eng	157,047	High	Chemical Eng	158,985	High
Cogn Sci/Biopsych	172,656	High	Biochemical Sci	173,973	High
Biomedical Eng	182,920	High	Molecular Biology	211,753	High
Health/Med Prep Prog	232,146	High	Actuarial Sci	234,645	High
Neuroscience	235,571	High			

Note: Earnings potential is computed as the median earnings among White males aged 43–57 who report a degree in that field. The data is from the American Community Survey, 2009-2021. Detailed majors are grouped into four income groups comprising roughly 25% of total employment each.

Table A.2: Residual Earnings Gap Decomposition: Between and Within Fields of Study, by Sex and Birth Cohort

		Reference Earnings Group:			
		White		Black/Hispanic	
Earnings Gap	**Total**	**Sorting**	**Within Major**	**Sorting**	**Within Major**
	(1)	(2)	(3)	(4)	(5)
Black-White					
Men	-0.244	-0.032	-0.212	-0.034	-0.210
		(13.01%)	(86.99%)	(13.89%)	(86.11%)
Women	-0.096	0.008	-0.105	-0.012	-0.085
		(-8.72%)	(108.72%)	(12.06%)	(87.94%)
Cohort 1955–74	-0.179	-0.023	-0.156	-0.029	-0.150
		(13.06%)	(86.94%)	(16.41%)	(83.59%)
Cohort 1975–94	-0.134	-0.008	-0.127	-0.016	-0.118
		(5.84%)	(94.16%)	(12.04%)	(87.96%)
Hispanic-White					
Men	-0.122	-0.015	-0.107	-0.015	-0.108
		(12.45%)	(87.55%)	(12.04%)	(87.96%)
Women	-0.064	-0.007	-0.058	-0.010	-0.054
		(10.33%)	(89.67%)	(15.79%)	(84.21%)
Cohort 1955–74	-0.090	-0.017	-0.073	-0.016	-0.074
		(18.99%)	(81.01%)	(18.12%)	(81.88%)
Cohort 1975–94	-0.094	-0.010	-0.084	-0.010	-0.084
		(10.98%)	(89.02%)	(10.85%)	(89.15%)

Note: The table decomposes the gap in average residual earnings between Black/Hispanic and White workers, indicated in Column (1), into the *sorting* component, reflecting differences in field of study composition, and the *within major* component, reflecting differences in residual earnings by race/ethnicity within fields of study. The decomposition is implemented separately by sex and birth-cohort subgroups. The analysis is based on 170 detailed field of study categories available in the American Community Survey (ACS) data. Columns (2) and (3) use the formula in Equation (1), which uses average residual earnings of White workers as the reference category; Columns (4) and (5) use the formula in Equation (2), which uses average residual earnings of Black/Hispanic workers as the reference category. The numbers in parenthesis indicate the fraction of the total that each component accounts for. The sample consists of U.S.-born, full-time, full-year workers aged 22–64, with at least a Bachelor's degree. Residual earnings are obtained from a regression of log real annual wage and salary income on sex, age and age squared, interaction terms between these variables, indicator variables for marital status, education level, and for reporting two BA degree fields, and a set of fully interacted commuting zone-by-year fixed effects. The data is from the ACS, 2009–2021.

Table A.3: Decomposition of Within-Major Residual Earnings Gap: Between and Within Occupations, by Sex and Birth Cohort

	Reference Earnings Group:					
	White			**Black/Hispanic**		
Within-Major Earnings Gap	**Total** (1)	**Sorting** (2)	**Within Occ** (3)	**Total** (4)	**Sorting** (5)	**Within Occ** (6)
Black-White						
Men	-0.212	-0.072 (34.01%)	-0.140 (65.99%)	-0.210	-0.086 (41.11%)	-0.124 (58.89%)
Women	-0.105	-0.032 (30.92%)	-0.072 (69.08%)	-0.085	-0.032 (38.21%)	-0.052 (61.79%)
Cohort 1955–74	-0.156	-0.062 (39.88%)	-0.094 (60.12%)	-0.150	-0.066 (44.37%)	-0.083 (55.63%)
Cohort 1975–94	-0.127	-0.042 (33.45%)	-0.084 (66.55%)	-0.118	-0.053 (45.20%)	-0.065 (54.80%)
Hispanic-White						
Men	-0.107	-0.036 (33.94%)	-0.071 (66.06%)	-0.108	-0.053 (49.15%)	-0.055 (50.85%)
Women	-0.058	-0.025 (42.74%)	-0.033 (57.26%)	-0.054	-0.025 (46.94%)	-0.029 (53.06%)
Cohort 1955–74	-0.073	-0.025 (34.79%)	-0.047 (65.21%)	-0.074	-0.044 (59.36%)	-0.030 (40.64%)
Cohort 1975–94	-0.084	-0.022 (25.87%)	-0.062 (74.13%)	-0.084	-0.034 (40.95%)	-0.049 (59.05%)

Note: The table decomposes the within-field-of-study gap in average residual earnings between Black/Hispanic and White workers, indicated in Column (1) and (4), into the *sorting* component, reflecting differences in occupational composition (conditional on field of study), and the *within occupation* component, reflecting differences in residual earnings by race/ethnicity within occupations (conditional on field of study). The decomposition is implemented separately by sex, education group, and birth-cohort subgroups. The analysis is based on 170 detailed field of study categories and 479 occupation categories available in the American Community Survey (ACS) data. Columns (2) and (3) use the formula in Equation (5), which uses average residual earnings of White workers as the reference category; Columns (5)–(6) use the formula in Equation (6), which uses average residual earnings of Black/Hispanic workers as the reference category. The numbers in parenthesis indicate the fraction of the total that each component accounts for. The sample consists of U.S.-born, full-time, full-year workers aged 22–64, with at least a Bachelor's degree. Residual earnings are obtained from a regression of log real annual wage and salary income on sex, age and age squared, interaction terms between these variables, indicator variables for marital status, education level, and for reporting two BA degree fields, and a set of fully interacted commuting zone-by-year fixed effects. The data is from the ACS, 2009–2021.