NBER WORKING PAPER SERIES

THE CONTRIBUTION OF COLLEGE MAJORS TO GENDER AND RACIAL EARNINGS DIFFERENCES

Scott A. Imberman
Michael F. Lovenheim
Patrick Massey
Kevin M. Stange
Rodney J. Andrews

Working Paper 34726
http://www.nber.org/papers/w34726

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
January 2026

We gratefully acknowledge that this research was made possible through data provided by the University of Texas at Dallas Education Research Center. The conclusions of this research do not necessarily reflect the opinions or official positions of the Texas Education Agency, the Texas Higher Education Coordinating Board, the Texas Workforce Commission, or the State of Texas. The research reported here was supported, in whole or in part, by the Institute of Education Sciences, U.S. Department of Education, through grant R305B200009 to Michigan State University. The opinions expressed are those of the authors and do not represent the views of the Institute or the U.S. Department of Education. We thank Fran Blau and seminar participants at Brookings Institution, CESifo Economics of Education Conference, Cornell University, Harvard University, McGill University, the NBER Race and Stratification Working Group, the Norwegian School of Economics, Notre Dame, Syracuse University, the University of Georgia, the University of Pennsylvania, and the University of Virginia, for helpful comments and suggestions. † Rodney Andrews tragically and unexpectedly passed away early in the writing of this paper and was a major contributor to the intellectual framing and analysis that this work builds on, not to mention a dear friend. This paper is dedicated to his memory. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

The Contribution of College Majors to Gender and Racial Earnings Differences
Scott A. Imberman, Michael F. Lovenheim, Patrick Massey, Kevin M. Stange, and Rodney J. Andrews
NBER Working Paper No. 34726
January 2026
JEL No. I23, I26, J24

ABSTRACT

Gender and racial/ethnic gaps in labor market earnings remain large, even among college-goers. Cross-gender and race/ethnic differences in choice of and returns to college major are potentially important contributors. Following Texas public high school graduates for up to 20 years through college and the labor market, we assess gender and racial differences in college major choices and the consequences of these choices. Women and underrepresented minorities are less likely than men, Whites, and Asians to major in high earning fields like business, economics, engineering, and computer science, however we also show that they experience lower returns to these majors. Differences in major-specific returns relative to liberal arts explain about one quarter of the gender, White-Black, and White-Hispanic (but not White-Asian) earnings gaps among four-year college students and become larger contributors to earnings gaps than differential major distributions as workers age. We present suggestive evidence that differences in occupation choices within field are a key driver of the differences in returns across groups. The work shines light on the roles that college major choice and returns by gender and race contribute to inequality.

Scott A. Imberman
Michigan State University
and NBER
imberman@msu.edu

Michael F. Lovenheim
Cornell University
Brooks School of Public Policy
Department of Policy Analysis
and Management,
and ILR School
Department of Economics
and NBER
mfl55@cornell.edu

Patrick Massey
Michigan State University
pmassey@msu.edu

Kevin M. Stange
University of Michigan
Gerald R. Ford School of Public Policy
and NBER
kstange@umich.edu

Rodney J. Andrews
University of Texas at Dallas

I. Introduction

Gender and racial differences in labor market earnings are substantial, even among workers with four-year degrees (Bayer and Charles 2018; Blau and Kahn 2017; Chetty et al. 2020; Hirsch and Winters 2014; Sakamoto, Tamborini, and Kim 2018). In Texas, our data show that men who attended a four-year college earn 51% more than female college attendees in mid-career, while White college attendees earn 43% more than Black attendees and 30% more than non-Black Hispanic college enrollees. In contrast, Asian college attendees earn about 14% more than White attendees. Majors such as business, computer science, economics, engineering, science, and math have high average returns (Andrews et al. forthcoming; Arcidiacono, 2004; Hamermesh and Donald, 2008; Kirkebøen, Leuven and Mogstad 2016), and women and under-represented minorities (URMs)[1] are less likely to major in these fields (Arcidiacono, Aucejo, and Hotz 2016; Arcidiacono, Aucejo, and Spenner 2012; Black et al. 2008; Dickson 2010; England and Li 2006; Kugler, Tinsley, and Ukhaneva 2021; Sloane, Hurst, and Black 2021; Turner and Bowen 1999). College majors thus are a potentially important contributor to post-college labor market disparities by gender and race/ethnicity.

College major choice can impact earnings differences across groups through two channels. First, cross-group differences in the distribution of majors can drive earnings disparities because of the different average returns to majors. Second, there could be differences in group-specific returns to major choice. For example, women may earn less than men because they major in subjects that have a lower average return (major choice) or because they experience a lower return to majoring in certain areas relative to men (major returns). Equalizing the distribution of majors across groups, as many policy efforts aim to do, will not eliminate inequalities if this second pathway is substantial.

In this paper, we use linked administrative K-12, postsecondary, and unemployment insurance earnings records for all public high school graduates in Texas followed for up to 20 years after high school to examine how the distribution of majors and their group-specific returns contribute to subsequent earnings disparities by gender and race/ethnicity. We document the distribution of college majors by gender and racial/ethnic group, estimate the group-specific returns to college major, and conduct Blinder-Oaxaca-Kitagawa decompositions to quantify the

[1] We use the term "under-represented minorities" to refer to non-Hispanic Black and Hispanic students.

role of these two channels. Our analyses rely on rich controls for pre-collegiate academic characteristics, such as test scores and SES, as well as fixed effects for high school and college attended. These control are the same that were used in Andrews et al. (forthcoming) to estimate the return to college majors overall and more extensive than the factors accounted for in prior research studying the contribution of college major choices in the US to gender and racial/ethnic earnings differences.

We find that the distribution of college majors explains relatively little of mid-career gender and racial earnings gaps. Early in a career, differences in major choices by gender can explain 86% of the residual earnings gaps but little of the earnings differences across racial/ethnic groups. As we examine earnings farther out, the explanatory power of major choice falls for most groups: by mid-career, differences in college major choice explain just 16% of the earnings gap by gender, 5% of the White-Black earnings gap, and 10% of the White-Hispanic earnings gap. In contrast, college major choice explains 63% of White-Asian earnings differences at mid-career.

On the other hand, we document substantial differences in the *returns* to college major across groups, with differences growing over the lifecycle. We define returns as the difference between earnings in a given major for a specific group and earnings in liberal arts (the reference category) for that group. Most prior research has implicitly assumed that returns relative to others in the same group are constant across demographic categories, which has led to a focus on the differences in major choices as a contributor to earnings gaps among college graduates. But if women and URMs face lower relative returns in majors with high average earnings, then differences in major choices will be less important for explaining earnings gaps.

Focusing on STEM and higher earning fields (biology & health, business, computer science, engineering, economics, science & math) in mid-career (16-20 years after high school), we estimate that women experience quarterly returns in each field relative to liberal arts that range from $1,101 to $4,564 below returns for men, equivalent to 8% to 34% of mean quarterly earnings for women in our sample during this career stage. Using estimates from Wiswall and Zafar (2015) of the elasticity of major choice with respect to earnings expectations, we calculate that under rational expectations and full information these differences in returns can explain a sizable portion of the under-representation of women in these fields.

Similarly, Black and Hispanic students experience far lower returns than White students in many high-earning fields. Relative to White students' returns, Black students' returns at mid-career in the fields listed above range from $39 higher to $8,826 lower than for White students (-0.3% to 70% of mean Black earnings). Hispanic students' returns are between $2,879 and $6,788 lower than White students' (21% to 49% of mean Hispanic earnings). Using the Wiswall and Zafar (2015) estimates, these differences in returns can explain nearly all of the under-representation of Hispanic and Black students in majors associated with high earnings. White-Asian differences in returns are smaller but are sizable in several areas – between $485 and $7,127 lower than those for White students (2% to 34% of mean Asian earnings) in engineering, business, economics, and computer science. Asian students have higher returns than their White peers in biology & health ($1,848) and science & math ($1,565).

A Blinder-Oaxaca-Kitagawa (Blinder 1973; Oaxaca 1973; Kitagawa 1952) decomposition shows that differences in group-specific returns to major relative to liberal arts are more important than differences in the distribution of majors. Differences in returns explain about one quarter of the gender, White-Black, and White-Hispanic earnings differences at mid-career. White-Asian differences in returns are in the wrong direction to explain the higher earnings of Asian students, however.[2] While the explanatory power of major choices declines with potential experience, the role of differential returns either grows or remains large. Hence, simply equalizing the distribution of majors will have only a small impact on cross-group earnings differences in the long run. In order to address mid-career gender and racial/ethnic earnings disaparities, one must equalize the returns to college majors rather than the distribution of majors.

Finally, we examine potential mechanisms that might explain the lower returns to college major experienced by women and URM students, including differences in occupation, the distribution of earnings, labor force participation, college completion, and GPA, along with mechanical effects of major aggregation. We find the most support for occupational sorting differences within majors across groups being the core driver of returns gaps. Quantile treatment effect estimates also suggest that the differneces in returns we estimate occur across the

[2] This finding occurs because Asians earn more than Whites on average 16-20 years after college but experience lower group-specific returns to most majors, even though they are more highly represented in high-earning majors like economics and engineering.

distribution, not just at the top. This suggests that our results are not driven by the underrepresentation of women and URM students in the most high-paying jobs.

Our paper makes several contributions to the literature. We are the first to show gender- and racial/ethnic-specific returns to major choice, how these returns change with potential experience, and how they affect the distribution of earnings across groups. Prior research on earnings effects of majors has focused on average returns (e.g., Arcidiacono 2004; Bleemer and Mehta 2022; Kirkebøen, Leuven and Mogstad 2016).[3] Most closely related to our paper, Andrews et al. (forthcoming) use similar data and methods to estimate the return to college major by potential experience, effects on the distribution of earnings, and lifecycle utility returns across all students. Our relative contribution is to show how returns vary by race/ethnicity and gender as well as how these differential returns impact the evolution of earnings disparities across groups.

Second, our paper contributes to the large literature on the causes of differential earnings by gender and race/ethnicity in the labor market. Some prior research, discussed in more detail in Section II, shows that college major choices can explain a large portion of the gender wage gap. However, these papers typically are unable to disentangle college major choice from college quality and pre-collegiate academic achievement measures. No prior work examines this question with respect to race/ethnicity. We present new evidence in a setting that allows us to account for these other factors that cross-group differences in major choices, per se, have a small impact on earnings differences. Our results point to differential *returns* to college major as an important driver of earnings disparities by gender and race/ethnicity. This explanation for earnings differences has received little prior attention in the literature, and few studies have estimated differences in group-specific returns to major.[4] Our results suggest that differential returns by race/ethnicity and gender can explain a substantial proportion of cross-group earnings differences among college attendees.

Third, we provide a new potential explanation for the persistent under-representation of women and URM students in fields with high average returns, like engineering and economics.

[3] See Altonji, Blom, and Meghir (2012), Altonji, Arcidiacono, and Maurel (2016), and Lovenheim and Smith (2023) for reviews of the literature on the returns to field of study.

[4] Brown and Corcoran (1997) is one exception. Using a similar decomposition approach applied to workers in the SIPP and NLSY79, they find that majors explain a sizeable share of the gender wage gap and that women experience lower returns to completing high-return majors. They do not estimate how these differential returns contribute to the gender earnings gap, however, nor do they examine differences by race/ethnicity.

These groups experience lower returns to these fields relative to their other options, which reduces their attractiveness. Assuming rational expectations, differences in earnings returns can explain a sizable portion of the under-representation of women,[5] Black, and Hispanic students in business, economics, computer science, science & math, and engineering. Efforts to shift the major choices of under-represented groups to these fields may be unsuccessful if the role of differential returns is not addressed first.

II. Sources of Gender and Racial/Ethnic Differences in Earnings

a. Gender

Our paper contributes to a large body of prior work that explores the sources of differences in earnings by gender. Blau and Kahn (2017) provide a comprehensive review of gender wage gap research, showing that by 2010 women earned about 80% as much as men. They further demonstrate that educational attainment and experience can explain little of the gender earnings gap. However, they do not examine the role of college major and instead highlight the importance of gender differences in occupation, gender roles, and the division of labor between men and women as main sources of remaining earnings differences. This conclusion aligns with those of Goldin (2014), who argues that the final convergence of gender earnings gaps is likely to entail increased flexibility of jobs.

Women have higher average educational attainment than men and obtain postsecondary degrees at a higher rate (Goldin, Katz, and Kuziemko 2006), which is why educational attainment cannot explain gender earnings disparities. Beyond attainment, men and women continue to major in different subjects, with men more represented in technical fields that are associated with higher average earnings (Brown and Corcoran, 1997; Black et al. 2008; England and Li 2006; Dickson 2010; Gemici and Wiswall 2014; Kugler, Tinsley, and Ukhaneva 2021; Sloane, Hurst, and Black 2021; Turner and Bowen 1999). Several papers explore the role of field of study in driving the gender earnings gap. Using data from the American Community Survey (ACS), Sloane, Hurst, and Black (2021) show that major controls account for 32% of the male-

[5] Zafar (2013) uses survey data from Northwestern University to show that men and women have different preferences for workplace characteristics, including pay, which can generate differences in major selection. If women care less about the labor market returns to majors than men, we may overstate the role of differential returns in driving college major choice.

female wage gap. McDonald and Thornton (2007) find that college majors explain nearly 95% of differences in starting salary offers after college, while Black et al. (2008) use data from the National Survey of College Graduates to show that controlling for college major explains about 30% of the wage gap over and above what is explained by the highest degree earned.

Similar results have been found in Europe. Machin and Puhani (2003) show that college major explains a substantial portion of the gender wage gap in England and Germany, as do Britton, Dearden, and Waltmann (2021). Hägglund (2024) and Francesconi and Parey (2018) find similar results in Germany and Finland, while Humphries, Joensen, and Veramendi (2024) report that college major can explain 50–60 percent of the gender wage gap in Sweden. Both Humphries, Joensen, and Veramendi (2024) and Machin and Puhani (2003) present evidence that more detailed major controls explain a larger portion of the gender wage gap.

Our paper extends our understanding of the role of college major choice in driving the gender earnings gap in several ways. First, most of these papers do not control for pre-collegiate academic achievement levels or the college of attendance. This is problematic because without controlling for selection into majors or the correlation between college quality and major choice, one risks confounding the role of major with unobserved labor market productivity. We take a selection on observables approach to addressing selection into field of study, using a rich set of pre-collegiate, demographic, and academic achievement measures as well as high school and college fixed effects. These controls are the same as those used in Andrews et al. (forthcoming), which is the most comprehensive analysis of the returns to college majors in the US to date. We thus provide the first estimates in the US of how major choice affects gender earnings gaps that credibly account for selection into field of study.

We also contribute to this literature by providing the first estimates of how majors affect the time path of earnings inequality between men and women. Our main contribution is to show new evidence on the role played by differential returns to college major in the gender earnings gap. As discussed below, we define returns as the gender-specific effect of majoring in a given area relative to liberal arts. We show that the returns women experience relative to majoring in liberal arts are smaller than for men, especially in fields that have high earnings, such as engineering, computer science, business, and economics.[6] In the most similar prior study, Brown and Corcoran (1997) find that majors explain a sizeable share of the gender wage gap and that women earn lower returns for completing high-return majors, though many of their major-specific estimates are imprecise due to the use of small survey samples. They do not estimate how much of the gender earnings gap can be attributed to these differential returns, which is a central focus of our study.

b. Race/Ethnicity

Much research has focused on documenting and understanding trends in earnings disparities between Black and White workers as well as between Hispanic and White workers in the US. Existing studies focus either on average earnings differences or on parts of the earnings distribution that are unlikely to be populated by college graduates (Antman, Duncan, and Trejo 2023; Bayer and Charles 2018; Chetty et al. 2020; Hirsch and Winters 2014; Kospentaris and Stratton 2021**).** Using US Tax data, Bayer and Charles (2018) document a median White-Black earnings gap of about 50% in 2014. They also document an earnings difference of 39% at the 90th percentile of the distribution, which is one of the few data points on White-Black earnings differences among those likely to have a college degree. Antman, Duncan, and Trejo (2023) report mean White-Black earnings differences of 47% and 17% among men and women, respectively, and White-Hispanic earnings differences of 30% and 19% for men and women.

Given the large differences in educational outcomes by race/ethnicity, most of the research seeking to explain earnings differences across groups has focused either on educational attainment (Antman, Duncan, and Trejo 2023; Zhou and Pan 2023) or on pre-market educational achievement measures (Neal and Johnson 1996). Despite concerns that URM students are particularly under-represented in technical fields, to our knowledge no research exists on how major choice impacts racial/ethnic earnings differences among college attendees.

---

[6] This finding aligns with Sloane, Hurst, and Black (2021) and Corbett and Hill (2012), who show that women tend to sort into lower-paying occupations, conditional on major. Importantly, this occupation sorting would not necessarily cause a difference in the gender-specific returns to major choice. If women in every major sort into proportionally lower-paying occupations than men, it would not cause a relative decline in gender-specific returns. Relatedly, Altonji and Zhu (2025) show that women receive higher returns than men to majoring in engineering and business using GPA cutoffs in Texas. Their findings are relative to second choice majors, however. Adjusting for the difference between second choice majors between men and women, their results align with ours in showing lower returns for women to these majors relative to liberal arts.

Prior research on this question focuses on affirmative action policies and shows that these policies can contribute to under-representation in STEM fields, especially at highly selective universities (Arcidiacono, Aucejo, and Hotz 2016; Arcidiacono, Aucejo, and Spenner 2012). In addition, Bleemer and Mehta (2024) show that restricted major access from major eligibility cutoffs leads to lower representation of Black and Hispanic students in majors that have high average returns. Their results suggest that these major restrictions have increased racial stratification in the returns to attending a given institution, but they do not examine whether under-represented groups experience the same returns as do majority students. Our findings suggest that because URM students have lower returns than White students in majors where average earnings are high, differences in major representation have only a small impact on racial and ethnic earnings gaps. Instead, our results point to a larger role for differential returns within majors across racial/ethnic groups in explaining earnings gaps among college attendees.

Finally, we examine differences in earnings between White and Asian workers. White-Asian earnings differences have not been a focus of prior research. We provide new evidence on differences in earnings between White and Asian workers as well as the role of college choice, pre-collegiate academic achievement, and field of study on these earnings differences.

III. Data and Descriptive Statistics

a. Data

We estimate the labor market returns to college majors by sex and gender for a half-million students using administrative data from three sources: the Texas Education Agency (TEA), the Texas Higher Education Coordinating Board (THECB), and quarterly earnings from the Texas Workforce Commission (TWC). These data follow all Texas students from public secondary school through college and into the workforce, provided individuals remain in Texas and attend public colleges and universities.

The construction of our analysis sample closely follows Andrews et al. (forthcoming); the details of the sample are described in Appendix B of that paper. We focus on all public high school graduates in Texas from 1996-2005 who enrolled in a four-year institution in the state. To capture the most salient postsecondary experience to employers when students end their education, we assign students to an institution and major based first on their highest degree earned and then based on their most recent enrollment. Any students who earn a bachelor's degree (BA or BS) at a Texas institution are included in the sample. Students who earned an associate's degree (AA or AS) but no bachelors are considered two-year students and are excluded, even if they enrolled in a four-year institution before or after earning an AA. Our assumption is that those students' associate's degrees will be more salient to employers than their four-year enrollment that did not lead to a credential. Students who do not earn a bachelors or associate's degree and whose last sector of enrollment is in the four-year sector are included in our analysis sample. This ensures that we are focusing on the most observable and recent degree or enrollment information that employers may see and that likely determines the skills workers bring to the labor market. Focusing on college attendees rather than completers also ensures that we do not endogenously restrict our sample, as major choice itself could impact completion. We provide results for completers only in the online appendix and show that they are similar.

Students' majors are assigned first based on major of their highest degree and then, for non-completers, based on last observed major. We aggregate four-year students into one of 14 major groups based on a combination of their specific 2- and 4-digit CIP codes[7] – agriculture, architecture, biology & health, business, communications, computer science, economics, engineering, interdisciplinary studies,[8] liberal arts, sciences & math, social science (excluding economics), vocational, and undeclared.[9] The college of attendance is measured as the institution at which the college major is determined using the method described above.

Labor market outcomes are constructed from quarterly earnings records through the last quarter of 2023 for every person who works in Texas, except for those who work for the Federal Government, the postal service, or are self-employed and thus are not covered by the state unemployment insurance system. Hence, we cannot distinguish between those who are unemployed, self-employed, not in the labor force, or working outside of Texas.[10] In general,

---

[7] The components of each major grouping can be found at the end of Online Appendix A (Table A-19).

[8] During the time these students were enrolled, Texas did not have a formal education major – students would take certain classes to qualify for a teaching certification and major in some other field. Most of these students, however, majored in "interdisciplinary studies," and thus we consider this to be a proxy for education majors.

[9] Students must declare a major to graduate, so undeclared students are comprised entirely of those who do not complete a four-year degree in Texas.

[10] Federal and postal employment are only a small portion of the Texas workforce, accounting for 1.9% of the workforce in January, 2025 (US Bureau of Labor Statistics, 2025). We thus assume that individuals with missing earnings data are either unemployed, out of the labor force, or work in a different state.

out-of-state attrition can bias estimates of earnings differences across institutions and fields, since migration tends to be correlated with earnings and is differential across programs (Foote and Stange, 2022). In prior work, we do not find such selection to be problematic (Andrews, Li and Lovenheim 2016; Andrews, Imberman and Lovenheim 2020; Andrews et al. forthcoming), likely because there is relatively low out-migration from Texas (Foote and Stange, forthcoming). We focus on earnings in three potential experience ranges: 6-10, 11-15, and 16-20 years after high school graduation.

In order to reduce bias associated with out-of-state migration, we only include quarterly earnings records that occur during students' "in-state employment window," which we define as the time spanning the first non-zero earnings record after leaving college and the last observed non-zero earnings record. This excludes any periods of non-employment immediately after school and at the end of our sample, which would capture those who have permanently left the state. We also exclude quarters in which students are enrolled in a postsecondary institution in Texas, which helps to ensure that we are not attributing low earnings during undergraduate or graduate enrollment to the major. While we are unable to observe enrollment in schools outside of Texas, this would bias our estimates only to the extent that some majors differentially sort to such institutions relative to in-state institutions for graduate study. Finally, we restrict earnings observations to at least 6 years after high school graduation to ensure that students have sufficient time to complete an undergraduate course of study.

Quarters with no earnings records that are within the in-state earnings window and meet our inclusion criteria are imputed to be zero and included in our earnings estimates. This approach is designed to address bias from out-of-state migration while still accounting for the extensive margin. However, we note that if individuals in Texas leave the labor market permanently, we will code them as having left the state rather than not working. Hence, we may miss some labor market exit driven by fertility, especially for women. This should reduce our estimates of the earnings disparities between men and women, especially in the 11 to 15 and 16 to 20 year potential experience groups when women are the most likely to have children (Livingston 2015). We show in Online Appendix A (Tables A-12 and A-13) that there is little scope for differences in the number of quarters worked or in permanently leaving the earnings sample to drive our results.[11] Earnings are converted to real 2016 dollars throughout the analysis.

One of the important contributions we bring to the literature is the ability to control for pre-collegiate academic achievement as well as college type. These controls have not been available in prior research examining the role of major in driving earnings disparities by gender and race/ethnicity due to small sample sizes. We control for math and reading exam scores that are given to all students in 10th grade in Texas. These are exit exam scores, and students in these cohorts were required to score above a certain threshold to receive a high school diploma. We standardize each score to have a mean of zero and a standard deviation of one in each year the test is given. We also control for whether the student is in the top decile or the 70th-90th percentiles of the within-high school and year distribution. The Texas Top 10 Percent Plan provides automatic admission to any postsecondary institution for any student in the top 10% of their class GPA distribution in these cohorts. We do not observe high school GPA, but these within-school exam percentiles are highly correlated with whether students are admitted under the Top 10 Percent Plan (Andrews, Imberman, and Lovenheim 2020).

We further control for whether a student is "at risk" of high school dropout, which combines information on course performance, grade advancement, test scores, limited English proficiency status, criminal justice system interaction, pregnancy, and homelessness. Finally, we control for whether a student is economically disadvantaged, defined as being eligible for free or reduced-price lunch, below the poverty line, or receiving TANF or SNAP.

b. Descriptive Statistics

Table 1 provides descriptive statistics for our analysis sample. The first part of the table presents evidence on differences in major choices by gender and race/ethnicity. Columns (1) and (2) show large differences in major choices between men and women. Women are less likely to major in subjects generally associated with higher earnings (e.g., business, computer science, economics, and engineering). There are race/ethnic differences in major choice as well, although they are smaller in magnitude than the gender differences. Relative to White students, Black and Hispanic students are less likely to major in business, economics, engineering, and liberal arts but are

[11] For example, other than for undeclared, the largest difference between male and females in number of quarters with positive earnings is 5.63 (bio/health) and for race is 3.05 (Asian vs. Hispanic for computer science). When looking at the likelihood of exiting the earnings sample, the largest gender difference is 0.05 (vocational) and for race is 0.09 (Black vs. White in Business).

more likely to major in biology and health and vocational. Critically, while Black and Hispanic students are under-represented in some technical subjects, they do not on average major in lower-earnings subjects than their White counterparts. In contrast, Asian students are much more likely to major in high-earnings subjects than their White counterparts, such as biology & health, business, computer science, economics, and engineering. These differences in major choice could explain much of the earnings gaps between Whites and Asians.

The remainder of Table 1 shows differences in the observed characteristics of each group as well as mean earnings 6-10, 11-15, and 16-20 years after high school. Men have higher math test scores than women on average but slightly lower reading scores. White and Asian students have higher math and reading scores than Hispanic and Black students, with Asian students having the highest math scores (at 0.81 sd) and White students having the highest reading scores (at 0.63 sd). Gender differences in the likelihood of being at risk or economically disadvantaged are small, while Black and Hispanic college students are much more likely to be at risk of dropout and economically disadvantaged than their White and Asian counterparts. These differences highlight the importance of controlling for pre-collegiate academic achievement in assessing the role of college majors in explaining earnings gaps.

The bottom of Table 1 shows raw means of earnings by gender and racial/ethnic groups for each time period post-HS, with male-female and each racial/ethnic group difference relative to White students shown in Table 2. Aligned with the substantial differences in pre-collegiate academic achievement and SES, there are large earnings gaps that grow over time between men and women as well as between White and Black and White and Hispanic students. Recall that these earnings are for those who attend (and mostly complete) a four-year degree, so these large earnings differences are notable. As shown in Table 2, men earn about 11% more than women 6-10 years after high school, which grows to 51% by 16-20 years after high school. In the early post-college period, White workers earnings are 25% higher than their Black peers and 18% higher than their Hispanic peers. They grow to 43% and 30% 16-20 years after high school, respectively. Relative to Asian workers, White workers earn 5% more in the early period after college but then earn 14% less by their mid-30s. Hence, the White-Asian earnings gap flips sign as people in the sample gain experience in the labor market, while the other earnings gaps we document get larger in magnitude.

Online Appendix Table B-1 replicates Table 2 for a national sample using the American Community Survey. The patterns align closely with those in Table 2, suggesting that the disparities we document and our results are likely to be broadly generalizable to the rest of the United States. We now turn to an examination of the role of college major choice in explaining these patterns.

IV. Empirical Methods

The goal of this paper is to understand how major choice and the differential returns to college major across groups can explain gender and racial/ethnic earnings differences. We approach this question in two ways. First, we estimate how adding controls for college major conditional on student background and college controls affects unexplained gender and racial/ethnic earnings gaps by relative experience. We then estimate group-specific returns in order to conduct linear decompositions that allow us to calculate how equalizing college major choices and major returns across groups would affect earnings differences. Below, we discuss each of these empirical approaches in turn.

a. Unexplained Cross-group Earnings Gaps

We begin by estimating the effect of controlling for major choice on unexplained earnings gaps across groups. We estimate a series of linear regression models of the form:

$$Y_{iscjk} = \beta Male/White_i + \mathbf{\Omega} \mathbf{X}_i + \sum_{k=2}^{14} \theta_k I(major_i = k) + \delta_{cs} + \gamma_{cj} + \epsilon_{iscjk}, \quad (1)$$

where Y_{iscjk} is an outcome for individual i, from high school s, in high school cohort c, attending postsecondary institution j, and majoring in field k. The coefficient of interest is β. When examining gender, β shows the difference in mean earnings between men and women, conditional on the observables. When focusing on race/ethnicity, β shows the difference in mean earnings between White and Black, Hispanic, or Asian college attendees. All standard errors are clustered at the postsecondary institution-by-major group level, reflecting the correlation of outcomes across students who attend the same college and major in the same subject area. Results are similar if we cluster by high school.

The full version of equation (1) includes the controls for pre-collegiate academic aptitude and student SES discussed in Section III and shown in Table 1. We also control for high school-by-cohort (δ_{cs}) and college-by-cohort (γ_{cj}) fixed effects. Because of geographic sorting and patterns of segregation by race/ethnicity and SES, one's high school incorporates a substantial amount of information about one's aptitude. Furthermore, the sorting of students into different colleges leads to smaller differences in unobservables across students within the same college and cohort than across students in different majors and different institutions. Finally, we include college major indicators, with liberal arts (k=1) as the excluded major category. We focus on indicators for the 14 major groups discussed in Section III and shown in Table 1, but we also show how the estimates change when we include dummies for each CIP-4 major and when we interact major groups with postsecondary institution (i.e., college programs).

To understand how the controls impact the unexplained portion of the earnings gap across groups, we add controls sequentially. We first control for pre-college factors: the X_i variables and the high school by cohort fixed effects. We next add college by cohort fixed effects, followed by our major controls. Hence, we show how much of the unexplained earnings difference can be accounted for by college majors, conditional on pre-collegiate academic achievement, SES, and postsecondary institution. These models are estimated separately for our three different time horizons: 6 to 10 years post-high school, 11 to 15 years post-high school, and 16 to 20 years post-high school.

b. Group-Specific Returns to College Major

The second part of our analysis seeks to estimate group-specific returns to college major choice and then decompose earnings differences across groups into the portions due to differential major selection and differential returns to major. For ease of exposition, we present our approach for gender differences. The analysis of racial/ethnic differences is similar: we estimate the model for all racial/ethnic groups together, with *Black* as the excluded category and interactions for each of the other racial/ethnic groups and major.

We estimate a version of equation (1) that include interactions between major and *Male*:

$$Y_{iscjk} = \alpha + \beta Male_i + \boldsymbol{\Omega X_i} + \sum_{k=2}^{14} \theta_k I(major_i = k) + \sum_{k=2}^{14} \phi_k I(major_i = k) * Male_i + \delta_{cs} + \gamma_{cj} + \epsilon_{iscjk}. \tag{2}$$

The coefficients of interest in equation (2) are θ_k and ϕ_k, which quantify the major returns for men and women. That is, θ_k shows the returns for women of a given major relative to women in liberal arts (the excluded category), while $\theta_k + \phi_k$ shows the returns for men to a given major relative to men in liberal arts. These parameters differ from gender-specific earnings differences across majors because they each are relative to gender-specific earnings in liberal arts. If men earn the same amount more than women in every major, then $\phi_k = 0$ for each k.

We use the estimates from equation (2) to decompose the earnings differences between men and women into the portion due to differential returns (ϕ_k) and the part due to the differences in major choice ($I(major_i = k) * Male_i$). For ease of exposition, define $Z_{iscj} = \boldsymbol{\Omega X_i} + \delta_{cs} + \gamma_{cj}$. These are the non-major controls in the model. Taking expectations, assuming constant coefficients on $\mathbf{Z}$, and keeping i as the only non-major subscript, we can write the earnings equation for men and women, respectively, as:

$$E(Y|Male) = \alpha + \beta + \boldsymbol{\Psi E}(\boldsymbol{Z_i^m}) + \sum_{\boldsymbol{k=2}}^{\boldsymbol{14}} (\theta_k + \phi_k) P(major = k)^m \qquad (3)$$

$$E(Y|Female) = \alpha + \boldsymbol{\Psi E}(\boldsymbol{Z_i^f}) + \sum_{\boldsymbol{k=2}}^{\boldsymbol{14}} (\theta_k) P(major = k)^f, \qquad (4)$$

assuming $E(\epsilon_{iscjk})|Male = E(\epsilon_{iscjk})|Female = 0$. The mean earnings difference between men and women can be written as:

$$\begin{aligned}
&E(Y|Male) - E(Y|female) \\
&= \beta + \boldsymbol{\Psi}[\boldsymbol{E}(\boldsymbol{Z_i^m}) - \boldsymbol{E}(\boldsymbol{Z_i^f})] \\
&\quad + \sum_{\boldsymbol{k=2}}^{\boldsymbol{14}} [(\theta_k + \phi_k) P(major = k)^m - (\theta_k) P(major = k)^f] \\
&= \beta + \boldsymbol{\Psi}[\boldsymbol{E}(\boldsymbol{Z_i^m}) - \boldsymbol{E}(\boldsymbol{Z_i^f})] \\
&\quad + \sum_{\boldsymbol{k=2}}^{\boldsymbol{14}} [(\theta_k + \phi_k) P(major = k)^m - \theta_k P(major = k)^f + (\theta_k \\
&\quad + \phi_k) P(major = k)^f - (\theta_k + \phi_k) P(major = k)^f] \\
&= \beta + \boldsymbol{\Psi}[\boldsymbol{E}(\boldsymbol{Z_i^m}) - \boldsymbol{E}(\boldsymbol{Z_i^f})] \\
&\quad + \sum_{\boldsymbol{k=2}}^{\boldsymbol{14}} [(\theta_k + \phi_k)(P(major = k)^m - P(major = k)^f) \\
&\quad + (\phi_k) P(major = k)^f]. \qquad (5)
\end{aligned}$$

In the last part of equation (5), $\sum_{k=2}^{14}(\theta_k + \phi_k)[P(major = k)^m - P(major = k)^f]$ shows the effect on earnings differences of equalizing the distribution of majors by gender, and $\sum_{k=2}^{14}(\phi_k)P(major = k)^f$ shows the effect of equalizing the returns to major, relative to gender-specific earnings in liberal arts. The unexplained portion is due to the controls included in $\mathbf{Z}$ and factors not included in the model (β). In addition to gender, we conduct these decompositions for each race/ethnicity compared to Whites.

The assumptions of this Blinder-Oaxaca-Kitagawa decomposition are that the controls in the model are sufficient to account for selection of different groups into different majors. Put another way, conditional on the controls the unobserved earnings capacity of each group is the same within each major. We emphasize that we have a larger set of controls for pre-collegiate academic achievement than has been used in most of the returns to college major literature and most certainly in prior work that has sought to estimate the contribution of college majors to cross-group earnings differences. These assumptions also are similar to those invoked in Andrews et al. (forthcoming) in their analysis of the returns to college major choice averaged over all students in Texas.

The choice of the excluded category in linear decompositions with categorical variables is arbitrary and can affect the portion of the earnings gaps explained by differential returns (Fortin, Lemieux, and Firpo 2011). The results of such decompositions thus are relevant for a specific counterfactual, in this case the excluded liberal arts major group.[12] We argue that this is a relevant counterfactual for several reasons. First, liberal arts is effectively comprised of "default" majors many students start in and that include most of the content of a traditional liberal arts curriculum. The other major groups are more specialized, and thus one can interpret differences between each major and liberal arts as the returns to specializing in a given area. Second, the liberal arts major is popular among all groups (see Table 1), making it a relevant reference category. And third, most of the rest of the literature uses liberal arts majors (in part or in whole) as the reference category, which makes our results easier to compare with prior work.

[12] This would not be the case if we included β in the decomposition. However, this coefficient includes both differential earnings by gender in liberal arts as well as aggregate lower earnings among women across all majors. Including β thus overstates the role of majors, as it attributes all lower earnings among women for reasons that are unrelated to the other observables to majors. When we include β in the decompositions, we find that differential "returns" explain a larger portion of the earnings gaps for race and gender, especially in the second two periods. The results are qualitatively similar to what we present below, however.

Using liberal arts as the excluded category is predicated on gender and racial/ethnic patterns in this major group being similar to what we document for the overall sample. If, for example, women earned substantially more than men in this major, then relative comparisons would be hard to interpret. Online Appendix Table A-1 replicates Table 2 for the liberal arts sample. Aside from women earning slightly more than men in the 6-10 years post-HS period, the pattern of earnings disparities for liberal arts matches those for the overall sample closely. Most of the gender and racial/ethnic differences are muted relative to Table 2, however. Hence, as we show below, the other majors exacerbate the cross-group earnings disparities that exist for liberal arts majors rather than generating substantively different earnings patterns.

This decomposition provides somewhat different information from the unexplained cross-group earnings gap analysis. The latter estimates how much of the earnings differences across groups we can explain with our extensive set of controls, including majors. This type of analysis is highly sensitive to the order in which you put in variables because of the correlation structure between the controls. We include majors last, which shows how much of the earnings gaps residual to background controls, HS fixed effects, and college fixed effects can be accounted for by majors. This likely understates the importance of majors, since these variables are correlated with one another. In contrast, the Blinder-Oaxaca-Kitagawa decomposition is valuable because it allows us to tease out the independent effects of college major and the returns to college major. The first analysis thus answers the question of how much of the earnings gap residual to the other controls can be accounted for by college major choices, while the decomposition answers the question of what earnings differences would look like if we equalized college major choices or returns across groups.

V. Results

a. Unexplained Cross-group Earnings Gaps

Table 3 presents the β estimates from equation (1) for male-female earnings differences. We first show the raw earnings difference in column (1), after which we add controls for observed characteristics and high school-cohort fixed effects in column (2) and then college-cohort fixed effects in column (3). Column (4) includes indicators for the 13 college major groups on which we focus. We then explore the role of more finely controlling for major and college type by including interactions between college major group and college fixed effects in column (5) and controlling for CIP4 major fixed effects in column (6). Panel A presents estimates for earnings 6-10 years after high school, Panel B shows estimates for earnings 11-15 years after high school, and Panel C presents results for earnings 16-20 years post high school.

Table 3 reports a raw earnings gap of $808 in Panel A, $3,688 in Panel B, and $6,954 in Panel C. As shown in Table 2, the gender earnings differences grow with potential experience. Including the vector of controls, including high school by cohort fixed effects (column 2) diminishes this gap by 27% in the early period but only by 12%-13% in the later two periods. Adding college-cohort fixed effects has only a slight effect on explaining the residual earnings differences, increasing the explained gender earnings gap to 29% in the early period and 14% and 13% in Panels B and C, respectively. Pre-collegiate academic achievement, SES, and college type thus explain almost a third of the early-career earnings differences between men and women but less than one sixth of the gender gap as workers gain experience in the labor market.[13]

Prior work has focused on differences in the distribution of majors across genders as a major contributor to the gender earnings gap, since women are underrepresented in higher-paying fields of engineering, computer science, business, and economics. Including major fixed effects in column (4) explains 78% of the gap in earnings 6-10 years after high school, which is an increase of 49% of the explained percentage relative to the other controls. This is aligned with prior evidence that college major differences can explain most of the gender gap in starting salaries (McDonald and Thornton 2007). After this early career period, however, major choice becomes less important for explaining gender earnings differences: majors account for an additional 17% of the earnings gap 11-15 years post-HS and 11.6% 16-20 years after high school, above and beyond what is explained by the other controls. Hence, differences in major shares are a decreasingly important explanation for gender differences in earnings as workers age. In Panels B and C, major choice has less explanatory power for gender earnings gaps than has been found in the prior literature, which likely is due to the ages at which prior researchers have observed earnings and the lack of academic achievement, SES, and college type controls in prior analyses.

[13] Reber et al. (2025) find that differences in high school GPA and course-taking explain a large portion of the gender gap in postsecondary enrollment. Our results suggest that pre-collegiate academic achievement factors play a more modest role in determining earnings differences by gender.

Including controls for college major program more flexibly – with institution by major fixed effects or additionally controlling for the specific 4-digit CIP major code – does not explain much more of the residual gender earnings gap. The latter model controls for differences in the specialization within broad field, for instance between marketing and finance within business, which could differ by gender. Allowing the effect of majors to vary by institution or further disaggregating majors does not explain more of the earnings differences between men and women in any time period.

Because women are more likely to take time out of the labor force to have and raise children, our inclusion of imputed zero earnings may be an important component of these results. Online Appendix Table A-2 shows estimates using only positive earnings quarters. The results are almost identical to those in Table 3.

Table 4 provides a similar analysis of racial/ethnic earnings differences, with White-Black differences in columns (1)-(3), White-Hispanic differences in columns (4)-(6), and White-Asian differences in columns (7)-(9). We show estimates with no controls, all controls and fixed effects, and all controls and fixed effects with college major in Table 4. The other specifications shown in Table 3 for gender are presented for race/ethnicity in Online Appendix Table A-3.

There is a large White-Black raw earnings gap in each period: $1,673 6-10 years after high school, $3,237 11-15 years after high school, and $5,423 16-20 years after high school. As discussed in Section III, these gaps grow in percentage terms as well as in levels. Aligned with the findings in Neal and Johnson (1997), controlling for pre-collegiate academic achievement and college fixed effects explains about three quarters of the earnings differences in each period. Most of the Black-White earnings differences thus can be explained by where students attend college, pre-collegiate academic achievement, and SES measures.

Adding in major controls has no additional explanatory power for any relative experience group. Indeed, the explained portion declines when we add in major controls and does not change when we more flexibly control for major (Table A-3). This result occurs because Black students, on average, major in higher earning areas than White students. For example, the proportion of Black students majoring in liberal arts is lower and the proportion majoring in biology and health and vocational is higher. These findings are novel in showing that while Black-White earnings differences are strongly related to academic achievement and college quality, field of study actually pushes earnings in the direction of reducing the earnings gap. On average, these results suggest that Black students are not majoring in lower-earnings subjects.

Columns (4)-(6) of Table 4 presents results for White-Hispanic earnings differences. Hispanic college attendees earn less than White college attendees in each period: $1,285 6-10 years after high school, $2,414 11-15 years after high school, and $4,179 16-20 years after high school. These differences grow with potential experience, both in levels and proportionally in relation to mean White earnings. The pre-collegiate controls and college fixed effects explain a large proportion of these earnings differences, at 97% in Panel A, 84% in Panel B, and 77% in Panel C. These variables thus explain even more of the Hispanic-White earnings differences than they do the Black-White earnings differences.

Controlling for college major has little impact on the unexplained portion of the White-Hispanic earnings gap in any of the relative experience periods. In the earliest period the explained percentage increases slightly, but it declines in the other two periods. As with the Black-White comparison, more flexibly controlling for major and controlling for college program does not increase the explanatory power of majors (Table A-3).

We report results for White-Asian earnings differences in the final three columns of Table 4. Raw White-Asian earnings differences are positive 6-10 years after high school at $361 and then turn negative (Asians earning more than Whites) at -$1,184 and -$2,972 11-15 and 16-20 years after high school, respectively. Because Asian students on average have higher pre-collegiate academic achievement than Whites (Table 2) and attend more-selective universities, controlling for pre-collegiate observables and college fixed effects reduces the Asian earnings premium in Panels B and C, explaining 88% and 65% of the earnings gap, respectively, while the White-Asian gap in Panel A expands. These results show that White students earn more than Asian students right after college despite having worse pre-collegiate academic achievement and attending lower-return colleges, while these factors explain most of the higher earnings among Asian students in 11-15 and 16-20 years after high school.

Asian students are more likely to major in subjects that have higher earnings relative to their White counterparts. Controlling for college major thus induces all of the White-Asian earnings differences to be positive, as is the case for White-Black and White-Hispanic gaps. Hence, for the 11-15 and 16-20 years post-HS groups, major choice more than fully explains the remaining earnings differences, while for the 6-10 years post-HS group it suggests an even larger positive earnings disparity in favor of White workers. Aligned with the results for Black and Hispanic workers, more flexibly controlling for major has little impact on the results and conclusions (Appendix Table A-3). The controls in our model combined with college major fully explain the fact that White students earn less than Asian students 11+ years after high school. Differences in major choice account for a non-trivial part of these earnings differences, which indicates that college majors are far more important in explaining White-Asian earnings gaps than they are for White-Hispanic and White-Black differences. In the earliest career period, our data show that White students earn more than Asian students, despite the fact that they have lower pre-collegiate academic achievement, attend lower-earnings colleges, and major in lower-earning subjects on average. Why White students earn more than Asian students early in their career is an important question that is due to factors beyond the scope of this study and that deserve more attention in subsequent research. Online Appendix Table A-4 shows that these results and conclusions are robust to only examining positive earnings quarters.

From this analysis, one might conclude that college major only plays a modest role in explaining longer-run earnings gaps among college attendees between men and women and between race/ethnic categories. These models, however, impose the strong assumption that the earnings *returns* to college major – how much more or less someone earns relative to a counterfactual major – are the same for men and women and by race/ethnicity. We now turn to an examination of differential returns by gender and race/ethnicity and assessment of how much these differences may matter for observed earnings gaps.

b. Gender and Racial/Ethnic Differences in Returns to College Major

Figures 1 and 2 show estimates of the θ_k and $\theta_k + \phi_k$ from equation (2) by gender.[14] These estimates are gender-specific returns, meaning they show the return for men (women) of majoring in field k relative to earnings in liberal arts for men (women). They thus measure the gender-specific earnings differences between field k and liberal arts (the excluded category). Note that this is different from earnings gaps by major, since these estimates are relative to own-gender earnings in liberal arts. If, for example, women earn less in every major than men, these

[14] Coefficients and standard errors for gender and racial/ethnic differences in returns to major choice are show in Online Appendix Tables A-5 (6-10 years), A-6 (11-15 years), and A-7 (16-20 years).

returns will not differ much by gender. No prior work has shown how returns to major choice vary by gender or race/ethnicity, though gender-specific returns, rather than earnings gaps, are the relevant factor in students' choice of major.

Throughout the rest of the paper, we show estimates separately for six higher-earnings majors (Figure 1: biology and health, business, economics, engineering, computer science, and science and math) and the six lower-earnings majors (Figure 2: agriculture, communications, architecture, social sciences, interdisciplinary studies, and vocational).[15] Note that STEM majors are all included in the first group. All estimates are relative to liberal arts, and we exclude undeclared majors from the figures as they all are college non-completers, though they are included in the regressions and estimates are provided in the online appendix.

The estimates in Figure 1 show that women experience lower returns versus liberal arts than men in many high-earning majors and that this gap grows with potential experience. The differences are large outside of science and math. Average relative returns in each of these areas are positive and large for both genders, but over time gender gaps grow to be substantial. By 16-20 years post-HS, male relative returns are $4,564 (38% relative to mean female earnings in liberal arts) higher in business, $2,871 (24%) higher in economics, $4,046 (34%) higher in biology & health, $2,614 (22%) higher in computer science, $2,461 (20%) higher in engineering, and $1,101 (9%) higher in science & math. Right after college, these gaps are much smaller and in the opposite direction for biology & health and science & math. In the 11-15 year post-HS period, returns for men grow relative to those for women in business, economics, and computer science, but they are much smaller than in the 16-20 year period. Hence, women experience lower long-run returns than men to these fields of study, but these gaps are modest in the period directly after college.

Substantial gender gaps in returns also are evident for lower-earnings majors, as shown in Figure 2. For agriculture, architecture, social sciences, interdisciplinary studies, and vocational, female returns are substantially below those for men 16-20 years after high school. Overall returns for these majors are lower than those in Figure 1, but the gender gaps still are sizable: 16-20 years post-HS, returns for women are $4,410 (37%) lower in agriculture, $841 (7%) lower in

[15] We use the estimates from Andrews et al. (forthcoming) to split majors in this way. For ease of exposition, we do not show results for undeclared, but they are presented in the online appendix tables.

architecture, \$1,372 (11%) lower in social science, and \$1,765 (15%) lower in interdisciplinary studies relative to men. The only major in which the return for women is higher than for men is communications, which is characterized by low overall returns. Aligned with the findings in Figure 1, the return gap grows substantially as workers age. Hence, the conclusions one can draw about differential returns to majors by gender depends on when earnings are measured. Shorter-run earnings estimates tell a different story from those measured farther out from college.

When we use logs to examine proportional differences in Online Appendix Figures A-1 and A-2 we see a more stable pattern of male returns being higher than female returns by a similar proportion in each period (outside of communications), although the differences are sometimes more modest in percentage terms (e.g. in economics, engineering, science, and – in the highest experience group – biology). Nonetheless, the patterns are qualitatively similar and show that women systematically experience lower returns to higher-paying majors than men. We focus on earnings levels for two reasons. First, we argue that levels estimates are more informative as they are proportional to the marginal utility gained from switching majors and reflect actual purchasing power from major choice. As shown in Andrews et al. (forthcoming), earnings differences in levels drive utility differences across fields, which are most relevant for decision making and long-run well-being. Second, proportional earnings differences are hard to interpret because they come off of different baseline levels. If men and women both experience similar proportional changes, this would lead women to experience much lower returns in levels because of their lower base earnings in liberal arts (Online Appendix Table A-1). Examining differential returns in levels is not dependent on the baseline earnings amounts, making them easier and more straightforward to interpret.

Can these differential returns explain the under-representation of women in high aggregate return fields like business and economics? To address this question, we use the elasticity of major choice with respect to earnings expectations from Wiswall and Zafar (2015). They report an elasticity of 0.07. Under rational expectations and full information, how much do the lower expected earnings for women because of these differential returns reduce the likelihood that they declare a major in a given area? Using the 16-20 post-HS estimates, we calculate that these differential returns reduce the likelihood that women major in business by 3.3 percentage points (off of a 6.0 pp gap), economics by 2.6 percentage points (off of a 1.2 pp gap), engineering by 1.5 percentage points (off of a 6.5 pp gap), computer science by 2.7 percentage points (off of a 2.5 pp gap), and science & math by 1.7 percentage points (off of a 0.8 pp gap). Admittedly, most students probably do not have full knowledge about the size of these gaps, and so we are unlikely to be in a full information environment. It also is likely that elasticities differ for men and women, which Wiswall and Zafar (2015) do not separately calculate. Nonetheless, these estimates highlight that the differences in returns experienced by men and women may explain a substantial proportion of the under-representation of women in many fields.

Similar estimates by racial/ethnic groups are shown in Figures 3 and 4 in levels and in Online Appendix Figures A-3 and A-4 in logs. Large differences in returns across racial ethnic groups are apparent. Focusing on White vs. Black student returns, Figures 3 and 4 show that Black students experience far lower returns than White students in the higher-earning fields of biology & health, business, computer science, economics, and engineering, and also in agriculture, communications, and vocational. As with gender, these differences tend to be small in the earliest period right after college but then expand substantially over time. Black students' returns 16-20 years after high school are $7,571 less than their White peers in engineering (71% of mean Black earnings in liberal arts), $4,132 (39%) lower for computer science, $1,099 (10%) lower for biology & health, $5,780 (55%) lower for business, $8,826 (83%) lower for economics, $3,080 (29%) lower for agriculture, and $1,765 (17%) lower for vocational 16-20 years after high school. For several majors, such as business, computer science, economics, engineering, agriculture, and vocational, sizable returns differences are evident 6-10 and 11-15 years after high school as well. Returns experienced by Black students are higher than for White students in interdisciplinary studies and social sciences.

These differential returns can fully explain the White-Black differences in the distribution of majors. Using the 0.07 elasticity with respect to expected earnings (Wiswall and Zafar 2015), differences in returns (again under rational expectations, homogenous elasticities across race, and full information) 16-20 years after high school reduce the likelihood Black students major in business by 4.5 percentage points (off of a 1.8 pp gap), economics by 7.0 percentage points (off 0.6 pp), engineering by 4.2 percentage points (off 2.1 pp), computer science by 4.5 percentage points (off 0.2 pp), and science and math by less than 0.1 percentage points (off 1.0 pp).

A similar pattern emerges for Hispanic students relative to White students. Hispanic students experience returns relative to their White counterparts that are $810 (7% relative to mean Hispanic earnings in liberal arts) lower in biology & health , $4,4449 (38%) lower in business, $2,879 (24%) lower in computer science, $6,788 (58%) lower in economics, $6,288 (53%) lower in engineering, $1,719 (15%) lower in science & math, $1,791 (15%) lower in agriculture, and $1,904 (11%) lower in vocational 16-20 years after high school. As with prior comparisons, gaps in these fields tend to expand over the career, with the exception of computer science, agriculture, and vocational where there are large gaps in all periods. Taken together, the evidence in Figures 3 and 4 point to large differences in the returns to college major between these two under-represented minority groups and White students, especially in subjects that have high average returns for White students. Black and Hispanic students do not experience as much of the earnings premiums conventionally associated with “high return” fields.

As with Black students, the lower returns experienced by Hispanic students can help explain their under-representation in several fields. Using the Wiswall and Zafar (2015) elasticity, returns 16-20 years after high school reduce the likelihood Hispanic students major in business by 3.5 percentage points (off of a 4.3 pp gap), economics by 5.4 percentage points (off 0.5 pp), engineering by 3.5 percentage points (off 0.5 pp), computer science by 3.1 percentage points (off 0.4 pp), and science & math by 3.0 percentage points (off 0.3 pp).

Returns to college majors are more mixed for Asian students relative to White students. For biology & health and sciences & math, Asian students have higher returns than White students, at $1,848 (11% relative to Asian mean earnings in liberal arts) and $1,564 (9%) 16-20 years post-HS, respectively. Relative returns in computer science are similar for Asian and White students, while for other majors there is a sizable return gap 16-20 years post-HS favoring White students: $3,096 (18%) in business, $7,127 (40%) in economics, $3,895 (22%) in engineering, $3,261 (19%) in agriculture, $2,316 (13%) in architecture, and $3,922 (22%) in communications. Because Asian students are more likely to major in business, computer science, economics, and engineering than White students, these differential returns do not contribute to relative White students’ under-representation in these areas.

The large differences by gender and race/ethnicity in the returns to major beg the question of whether there are similar differences by gender across racial/ethnic groups. Figures 5 and 6 show returns by gender interacted with race/ethnicity for high- and low-earning majors, respectively. Aligned with our prior findings, White men exhibit the largest returns relative to every other group for most majors. The gender differences for Black, Hispanic, and Asian students in returns are much smaller, although there is some evidence of larger returns for Hispanic men relative to Hispanic women in biology & health, business, computer science, and engineering. The main takeaway from these figures is that across majors, the largest returns to nearly all non-liberal arts majors flow to White men, and these return gaps grow substantially from early- through mid-career.

c. Decomposition: How Much of the Gap is Explained by Differences in Returns to Major?

Given the differences in returns to major across groups, we now decompose the gender and racial earnings gaps into the part that is due to differences in the distribution of majors versus differences in the group-specific returns to different majors, relative to liberal arts. We compute how much of the gender (racial) earnings difference at different ages would change if women (non-White students) had the same distribution of majors as men (White students) and, separately, if women (non-White students) had the same returns relative to liberal arts as men (White students). We use the raw gaps presented in Table 2 as the baseline differences that we seek to explain using the distribution of and returns to college major.[16] Table 5 reports these decomposition results, with Panel A showing results for gender and Panels B-D reporting for race/ethnicity.

Panel A first shows that, combined, the distribution of majors and differences in returns explain 99% of the small gap in years 6-10 after high school. This indicates that if women had the same returns to majors and the same major distribution as men, the gender gap would be eliminated in the years right after college. However, this pattern changes dramatically as we look further into individuals' careers when the gender gap increases, driven by a reduction in the role of major choice. By 16-20 years after high school, the explanatory power of the distribution of majors drops from 86% to 16% of the earnings gap. In contrast, the explanatory power of differences in returns to major choice grows over time. By 11-15 years post-HS, the role of

[16] We also could perform the same decomposition on the residual earnings gap presented in Tables 3 and 4 and would reach a similar qualitative conclusion, although the share explained by both the distribution and returns would be higher since the residual gap is smaller than the raw gap.

gender differences in the returns to major increases from 13% to 20% in explaining the gender gap in earnings, which grows further to 26% by 16-20 years after high school. Hence, in the later period when the earnings gap is large, gender differences in returns is a more important component of earnings differences than is major choice. The importance of differential returns in explaining the gender earnings gap has not been closely studied, especially in relation to the voluminous research on gender differences in the distribution of majors. Taken together, major choice and the returns to major explain 46% of the raw gender earnings gap 11-15 years post-HS and 42% 16-20 years after high school. Because the earnings gap increases with age, these factors explain a larger amount of the raw gender differences in earnings over time even though they explain a declining proportion of the gap.

Panel B shows that the distribution of college majors explains little of the White-Black earnings gap, especially 16-20 years after high school. Differences in majors most affect early-career earnings differences, but the explained proportion is small, at 16%. By 16-20 years after high school, differences in major explain less than 5% of the Black-White earnings gap. This is perhaps not surprising given the similar distribution of majors between Black and White college students shown in Table 1 and the insensitivity of the White-Black earnings gap to controlling for majors (conditional on the other controls) in Table 4. In contrast, race-specific differences in the returns to college major relative to liberal arts explain 30% of the Black-White earnings gap 6-10 years after high school, 23% 11-15 years after high school, and 27% 16-20 years after high school. Hence, if Black students had the relative returns of White students, the earnings gap would close by about a quarter. Black college students do not benefit as much from studying "high return" majors such as business, economics, computer science, and engineering (relative to liberal arts) as White students. Just equalizing the distribution of majors by race would do little the alter the Black-White earnings gap. The much larger source of earnings differences lies in the differential returns to studying more specialized college majors by race. Combined, college major explains 31% to 47% of Black-White earnings differences among college attendees.[17]

[17] Online Appendix Table A-8 shows decomposition estimates that switch the base category, using women instead of men and each non-White group instead of Whites. The pattern of results is qualitatively similar, with some differences in magnitudes. Differences in returns to major have more explanatory power for Black and Hispanic groups, and the role of major choice has less explanatory power. The role of returns among Asians is reduced somewhat in the first two earnings periods, while for gender the main difference is in the first earnings period where the role of returns is smaller and the role of major choice is larger.

Panel C tells a similar story for White-Hispanic earnings differences. College major choices explain little of the earnings gaps, from 25% in the earliest period to 10% in the latest period. As in Panel B, differential returns to college major have much larger explanatory power, explaining 53% of the Hispanic-White earnings gap 6-10 years, 37% 11-15 years, and 25% 16-20 years post-HS. Again, because the size of the gap rises with age, the absolute amount explained by differences in returns grows over time. Equalizing major distributions across White and Hispanic students would do little to alter earnings differences without equalizing the returns these students experience. Together, differences in majors and differences in the relative returns to major explain 34%-78% of the Hispanic-White earnings gap across periods.

The decomposition results thus far in Table 5 have several similarities across groups that are important to highlight. First, the percentage explained by differences in major choice are largest right after college, likely because employers do not have information about productivity from work experience and tenure at this point. This finding suggests that conclusions about the role of college major choice, per se, in driving cross-group earnings differences is sensitive to when earnings are measured. Second, starting in the 11-15 years after high school period, differences in the returns to college major relative to liberal arts become a more empirically relevant explanation for cross-group earnings differences. Third, the explanatory power of differential returns tends to grow with potential experience. Fourth, the absolute amount of earnings differences explained by differential returns grows with age, as the size of the gap increases substantially for all groups. These results thus point to group-specific relative returns as a key factor in understanding racial/ethnic and gender earnings disparities among college attendees in the long run.

The results for White-Asian earnings differences in Panel D differ from those for the other groups because Asian students major in subjects with higher earnings than their White peers on average and their average earnings are higher than White students in the second two periods. The results in Panel D show that both the distribution of majors and the returns to major are important for explaining these earnings differences, but they move in different directions in different time periods. In the earliest period, differences in major choices move in the "wrong" direction for explaining the earnings gap, as White students earn more on average than Asian students but Asian students major in higher-earning subjects. In the subsequent two periods, differences in major choices explain about 100% and 63% of the earnings differences, since Asian students earn on average more than White students. The role of differences in returns to majors is opposite in sign to the effect of major choice in each period. This result occurs because Asian students receive lower returns to most majors than White students, leading to a positive effect of return differences in the first period (when the gap is positive) and a negative effect in the second two periods (when the gap is negative). Put differently, if we equalized the return to majors between White and Asian students, Asian workers would earn even more than their White peers than they already do by 40-50% in the 11-15 and 16-20 post-HS periods.

The identification assumption underlying these results are that the controls and fixed effects are sufficient to address differential selection across groups into majors by potential earnings. To assess the robustness of our estimates to this assumption, in Online Appendix Table A-9 we show decompositions that include no controls and fixed effects and in Table A-10 we show results that include controls but no fixed effects. For gender, the estimates with no controls are larger than those in Table 5. Adding controls brings the estimates close to those in Table 5, suggesting that adding the array of fixed effects has little additional explanatory power. This result is driven by the fact that the controls in our models affect base earnings differences across groups but have little impact on earnings differences relative to liberal arts. Following the logic of Oster (2019), this suggests that there is little scope for residual selection in our estimates.

The results for Black and Hispanic (relative to White) decompositions also show larger explanatory power for majors in the regressions without controls. However, the estimates with only the control variables are smaller than those in Table 5, indicating that any selection residual to the control variables but addressed by the college and high school fixed effects go in the opposite direction. These results again suggest that the scope for residual selection on unobservables to drive our results is small and in this case potentially biases the estimates towards zero. For the Asian vs. White decompositions, the estimates are more mixed. Adding in fixed effects (relative to controls) has a small attenuating effect for the proportion explained by returns but increases the proportion explained by the distribution of majors. We argue that the results in Tables A-9 and A-10 reinforce the validity of our approach by showing that selection on unobservables would have to be much larger than the selection on observables to significantly bias our estimates.

VI. Potential Mechanisms

In this section, we discuss several potential mechanisms that could help explain our results. The mechanisms on which we focus are: 1) occupation selection, 2) distributional effects, 3) labor market participation differences across groups, 4) differences in completion, 5) differences in grade performance, and 6) aggregation of majors. We discuss evidence on each of these mechanisms in turn below. One important mechanism that we cannot examine is discrimination, although discrimination in labor markets could lead to differences in labor market participation or occupation selection and has been shown to influence women's major choices (Lepage, Li, & Zafar, 2025).

We start by examining occupational choice. The Texas administrative data do not contain information on occupation, so we turn to the American Community Survey (ACS). We use a national sample of college graduates from the 2009-2023 ACS who were 18 (and thus likely to graduate from high school) between 1996 and 2002 and were aged 24-38 when observed. These sample restrictions were imposed to align the ages and cohorts of the ACS sample with those examined in the Texas data, and we use a national, rather than state, sample to maximize statistical power.

We first calculate the raw difference in earnings in each time period relative to high school graduation between each major group and liberal arts for each demographic group. This is akin to the returns to college major calculated above, but without any controls. Despite the lack of controls, the same general patterns of lower relative returns for women, Black, and Hispanic students shown in Figures 1-4 are evident in these data. We next construct a counterfactual earnings difference that shows how relative earnings would change if we equalized the distribution of occupations between men and women and between White and non-White workers within each major, but holding the average earnings of each occupation fixed. Online Appendix B provides more information about the sample construction and this decomposition.

The results for earnings 16-20 years after likely high school graduation are shown in Online Appendix Table A-11, where we provide the actual differences and a counterfactual in which the occupational distributions are equalized.[18] These results provide suggestive evidence

[18] Estimates for 6-10 and 11-15 years after likely high school graduation are shown in Online Appendix Tables B-2 and B-3, respectively. Recall that Table B-1 shows mean earnings differences across groups and age for this national

that occupational choices are critical to understanding differences in major returns across groups. For example, in economics, male relative earnings are $6,013 higher than women's, and this difference is reduced to $488 (92%) if we were to equalize occupational choices by gender for economics majors. Similar effects are evident for White-Black (87%) and White-Hispanic (88%) earnings differences in economics. More generally, for business, economics, engineering, and computer science, occupational differences across groups can explain most of the relative earnings differences across groups by major. For biology & health, occupational differences explain over 100% of the male-female relative earnings differences but do not explain any of the White-Black or White-Hispanic differences. Outside of this major for these groups, differences in occupation conditional on major explain a large proportion of the lower returns experienced by women and non-White workers.

This evidence is only suggestive, since we are unable to control for pre-collegiate academic achievement and high school and college fixed effects as in our main results.[19] However, they indicate that occupation choices are a main driver of differential returns to college major. Understanding why occupational choices vary so much by race/ethnicity and gender within major is an important direction for future work.

Ultimately, we find that occupation choice is the only mechanism out of the possibilities listed above that explains a substantial portion of earnings gaps by gender or race/ethnicity. Turning to the other mechanisms, we start by examining distributional effects. The occupational differences could be due to high earners, which would mean that differential access to specific lucrative occupations is driving our results. We estimate unconditional quantile treatment effect (QTE) models that include the same control set used in our main estimates. The QTE models are estimated separately by gender and racial/ethnic group, comparing the (adjusted) distribution of earnings in each major to liberal arts within group.

Online Appendix Figures A-5 and A-6 show QTE estimates by gender and Figures A-7 and A-8 shows estimates by race/ethnicity. Two important patterns emerge from these data. First,

---

sample, The raw earnings differences align closely with those in Table 2, suggesting that the patterns we show in Texas generalize to the U.S.

[19] As discussed in Appendix B, we use SOC2 codes for occupations. Even at this relatively high level of aggregation, differences in occupation choice within major explain most of the cross-group differences in returns. We are unable to use less-aggregated occupation codes (e.g., SOC4) because within major and each demographic group many of the sample sizes for disaggregated occupations are too small.

for most majors and groups, differences in earnings appear throughout the distribution and do not spike at the top. This suggests that the returns differences we document are not driven by top earners. Second, the returns for women and for Black/Hispanic workers are low throughout much of the distribution. Hence, the mean returns come with substantial ex-ante risk for these populations, as a randomly chosen student is unlikely to experience those returns. Combined with the occupation decompositions, the QTE estimates suggest that earnings returns are driven by broad differences in occupation decisions by gender and race/ethnicity rather than being determined by decisions of top earners alone.

Next, we examine differences across groups in labor market participation. We estimate equation (4) using labor market participation measures as the dependent variable. Online Appendix Table A-12 shows the effect of major choice by gender and race/ethnicity on the number of quarters one is in the earnings sample, while Online Appendix Table A-13 shows the effect of major choice by group on the likelihood of leaving the earnings sample. Both tables show that there are no large differences by gender or race/ethnicity in the in-state relative labor force participation across majors, suggesting that any bias from differential selection into the earnings sample by major and group is likely to be small.[20]

Fourth, we examine the role of college completion: if women or URM students are less likely to complete college when they are enrolled in more technical majors, it could explain their lower returns. Online Appendix Tables A-14 through A-16 show estimates of the relative return to college majors by group among those who obtain a four-year college degree in our sample. In general, the estimates are similar to those for the full sample and indicate that completion differences across groups and majors cannot explain our results. To summarize these estimates and compare them with the baseline results, we calculate the ratio of the male-female (White-non-White) relative return difference for the completer sample versus the overall sample. This is effectively the percent difference between the completer sample and the overall sample in the difference in the relative returns across groups. We show the average across all majors and the average for high-earning majors: computer science, engineering, science & math, biology &

[20] Note that any overall participation differences between groups will be captured by the omitted major category; indeed, women in liberal arts have lower participation rates than men but this does not systematically differ across majors relative to men.

health, business, and economics. Ratios less than one align with differences in completion rates explaining some of the lower returns experienced by women and non-Whites.

The estimates generally are close to one, and in many cases are more than one, suggesting that differences in completion rates exacerbate the differences in returns that we document. There are some notable exceptions, however. Lower completion rates for Black students explain about 25% of the lower returns experienced by Black students 6-10 years after high school and explain 42% of the lower returns in high-earning majors. Lower completion likelihoods among Hispanic students in high-earning majors explains about 18% of the return difference relative to Whites in this period as well. A smaller but still notable amount of these gaps in the 11-15 year period also is explained by completion. However, by 16-20 years after high school, differences in completion rates do not explain any of the differences in returns across racial/ethnic groups. Hence, differences in completion likelihoods can only explain some of the early career racial/ethnic major returns differences and none of the gender differences.

Though primarily not driven by completion, the lower returns to college major experienced by women and URM students could be due to lower academic performance more generally. To examine this possibility, we estimate how major choice affects students' final grade point average, separately by gender and race/ethnicity. To drive our results, it would have to be the case that women or URMs in higher-earning majors have lower GPAs *relative* to those in liberal arts. We estimate a version of equation (2), using final GPA[21] as the dependent variable rather than earnings. Online Appendix Table A-17 presents the results. The differences in GPAs (relative to liberal arts) across groups are minor, typically less than 0.1 of a GPA point, indicating that this is unlikely to be a central explanation for our results.

A final potential mechanism is major aggregation: within our aggregate major categories, there may be cross-group differences in specific majors that translate to differences in returns. Note that the results in Tables 3 and A-3 suggest that this is not the case, as our estimates are robust to controlling for CIP-4 majors. In Online Appendix Table A-18, we conduct linear decompositions (equation 5) using CIP-4 majors rather than aggregate majors. We exclude any major with fewer than 30 individuals in each subgroup, which alters the baseline sample. Hence,

[21] The Texas Data do not directly provide a final GPA. We calculate a students' GPA as the summation of all grade points earned divided by the number of hours scheduled up until graduation. If a student has not graduated, then their GPA is calculated using all years observed.

we show the raw differences as well as the decomposition results using aggregate major groups for this sample. The results are similar to baseline, and the decompositions using more detailed majors align closely with the results that use aggregate major groups. These results suggest that our results and conclusions are not driven by aggregation.

VII. Conclusion

Using education and workforce administrative data from Texas, we present new evidence on how major choices differ between men and women as well as between White, Black, Hispanic, and Asian racial/ethnic groups. We then examine the consequences of these differences for explaining cross-group earnings gaps in three post-college periods: 6-10, 11-15, and 16-20 years after high school. We document how earnings gaps evolve in our data among those who attend a four-year college in Texas and how major choices impact earnings disparities as workers age.

We focus on two dimensions along which major choices can impact earnings differences across groups: differences in major choices per se and differences in major returns (relative to liberal arts) experienced by different groups. We present evidence that women experience much lower relative returns to high-earnings majors than do men, such as in computer science, engineering, business, economics, and biology & health. A similar story emerges for racial/ethnic earnings differences: Black and Hispanic students experience lower returns relative to White students to these majors that have high average returns. Using an elasticity estimate from the literature (Wiswall and Zafar 2015), we show that these differences in earnings returns can explain much of the under-representation of women and URMs in these majors.

We then present evidence from a linear decomposition that differences in earnings returns relative to liberal arts are a more important determinant of cross-group earnings differences than are major choices. Differences in majors are most important in the early career period, but once students reach their late 20s differences in the returns to major are the more dominant explanation for gender and racial/ethnic earnings gaps. For workers attending college in Texas 16-20 years after high school, differences in earnings returns explain about a quarter of the gender, White-Black, and White-Hispanic earnings disparities and move in the wrong direction to explain White-Asian earnings differences. Major choices and differential returns together explain 42% of the gender earnings gap, 31% of the White-Black earnings gap, 35% of the

White-Hispanic earnings difference, and 17% of the White-Asian earnings difference. Hence, college majors are an important determinant of earnings inequality by gender and race/ethnicity, with differential returns to major playing a large role especially as workers age. Finally, we present suggestive evidence that differences in occupation selection conditional on major is a key driver of differential returns by gender and racial/ethnic groups.

Our results have important implications for policies that can address racial and gender/ethnic labor market outcomes. They suggest that simply equalizing the distribution of majors between groups will have only a minor effect on earnings differences, particularly in the longer-run. Rather, what is needed is policies to equalize returns. Indeed, our results suggest that equalizing returns could eliminate or significantly reduce cross-group differences in major choice. One important source of differential earnings returns is occupational choices that may vary by gender and race/ethnicity conditional on college major. Policies to make high-earning occupations more inclusive also could reduce differences in returns across groups, although our results also show that differences in returns occur throughout the earnings distribution and are not just driven by high earners. Future work that examines the sources of these gender and racial/ethnic disparities in returns is important to more fully understand what policies can be used to reduce gender and racial/ethnic stratification in earnings.

References

Altonji, Joseph G., Erica Blom, and Costas Meghir. 2012. "Heterogeneity in Human Capital Investments: High School Curriculum, College Major, and Careers." *Annual Review of Economics* 4(1): 185-223.

Altonji, Joseph G., Peter Arcidiacono, and Arnaud Maurel. 2016. "The Analysis of Field Choice in College and Graduate School: Determinants and Wage Effects." In *Handbook of the Economics of Education*, vol. 5, pp. 305-396. Elsevier.

Altonji, Joseph G. and Zhengren Zhu. 2025. "Returns to and Option Value of Business and Engineering Majors." Working Paper.

Andrews, Rodney J., Scott A. Imberman, and Michael F. Lovenheim. 2020. "Recruiting and Supporting Low-income, High-achieving Students at Flagship Universities." *Economics of Education Review* 74: 101923.

Andrews, Rodney J., Scott A. Imberman, Michael F. Lovenheim, and Kevin M. Stange. Forthcoming. "The Returns to College Major Choice: Average and Distributional Effects, Career Trajectories, and Earnings Variability." *Review of Economics and Statistics*.

Andrews, Rodney J., Jing Li, and Michael F. Lovenheim. 2016. "Quantile Treatment Effects of College Quality on Earnings." *Journal of Human Resources* 51(1): 200-238.

Antman, Francisca M., Brian Duncan, and Stephen J. Trejo. 2023. "Hispanic Americans in the Labor Market: Patterns Over Time and Across Generations." *Journal of Economic Perspectives* 37(1): 169-198.

Arcidiacono, Peter. 2004. "Ability Sorting and the Returns to College Major." *Journal of Econometrics* 121(1): 343-375.

Arcidiacono, Peter, Esteban M. Aucejo, and V. Joseph Hotz. 2016. "University Differences in the Graduation of Minorities in STEM Fields: Evidence from California." *American Economic Review* 106(3): 525-562.

Arcidiacono, Peter, Esteban M. Aucejo, and Ken Spenner. 2012. "What Happens After Enrollment? An Analysis of the Time Path of Racial Differences in GPA and Major Choice." *IZA Journal of Labor Economics* 1: 1-24.

Arcidiacono, Peter, and Michael Lovenheim. 2016. "Affirmative Action and the Quality–fit Trade-off." *Journal of Economic Literature* 54(1): 3-51.

Astorne-Figari, Carmen and Jamin D. Speer. 2019. "Are Changes of Major Major Changes? The Roles of Grades, Gender, and Preferences in College Major Switching." *Economics of Education Review* 70: 75-93.

Bayer, Patrick and Kerwin Kofi Charles. 2018. "Divergent Paths: A New Perspective on Earnings Differences Between Black and White Men Since 1940." *Quarterly Journal of Economics* 133(3): 1459-1501.

Black, Dan A., Amelia M. Haviland, Seth G. Sanders, and Lowell J. Taylor. 2008. "Gender Wage Disparities Among the Highly Educated." *Journal of Human Resources* 43(3): 630-659.

Blau, Francine D. and Lawrence M. Kahn. 2017. "The Gender Wage Gap: Extent, Trends, and Explanations." *Journal of Economic Literature* 55(3): 789-865.

Blinder, Alan S. 1973. "Wage Discrimination: Reduced Form and Structural Estimates." *The Journal of Human Resources*, 8(4), 436-455.

Bleemer, Zachary and Aashish Mehta. 2022. "Will Studying Economics Make You Rich? A Regression Discontinuity Analysis of the Returns to College Major." *American Economic*

Journal: Applied Economics 14(2): 1-22.
Bleemer, Zachary and Aashish Mehta. 2024. "College Major Restrictions and Student Stratification." NBER Working Paper No. 33269.
Britton, Jack, Lorraine Dearden, and Ben Waltmann. 2021. "The Returns to Undergraduate Degrees by Socio-economic Group and Ethnicity." *Research Report*. Institute for Fiscal Studies. March 2021.
Brown, Charlie and Mary Corcoran. 1997. Sex-Based Differences in School Content and the Male-Female Wage Gap. *Journal of Labor Economics* 15(3.1): 431-465.
U.S. Bureau of Labor Statistics. (2025). *Current Employment Statistics*. https://www.bls.gov/data/#employment
Chetty, Raj, Nathaniel Hendren, Maggie R. Jones, and Sonya R. Porter. 2020. "Race and Economic Opportunity in the United States: An Intergenerational Perspective." *Quarterly Journal of Economics* 135(2): 711-783.
Corbett, Christianne, and Catherine Hill. 2012. *Graduating to a Pay Gap: The Earnings of Women and Men One Year after College Graduation*. American Association of University Women.
Dickson, Lisa. 2010. "Race and Gender Differences in College Major Choice." *The Annals of the American Academy of Political and Social Science* 627(1): 108-124.
England, Paula and Su Li. 2006. "Desegregation Stalled: The Changing Gender Composition of College Majors, 1971-2002." *Gender & Society* 20(5): 657-677.
Fortin, Nicole, Thomas Lemieux, and Sergio Firpo. 2011. "Decomposition Methods in Economics." In *Handbook of Labor Economics*, vol. 4, pp. 1-102. Elsevier.
Foote, Andrew and Kevin M. Stange. Forthcoming. "Attrition from Administrative Data: Problems and Solutions With an Application to Postsecondary Education." *Review of Economics and Statistics*.
Francesconi, Marco and Matthias Parey. 2018. "Early Gender Gaps Among University Graduates." *European Economic Review* 109: 63-82.
Gemici, Ahu and Matthew Wiswall. 2014. "Evolution of Gender Differences in Post-secondary Human Capital Investments: College Majors." *International Economic Review* 55(1): 23-56.
Goldin, Claudia, Lawrence F. Katz, and Ilyana Kuziemko. 2006. "The Homecoming of American College Women: The Reversal of the College Gender Gap." *Journal of Economic perspectives* 20(4): 133-156.
Hägglund, Anna Erika. 2024. "Same Degrees, Different Outcomes? Fields of Study Choices and Gender Wage Inequality in Finland and Germany." *Social Science Research* 122: 103029.
Hamermesh, Daniel S. and Stephen G. Donald, 2008. "The Effect of College Curriculum on Earnings: An Affinity Identifier for Non-ignorable Non-response Bias." *Journal of Econometrics* 144(2): 479-491.
Hirsch, Barry T. and John V. Winters. 2014. "An Anatomy of Racial and Ethnic Trends in Male Earnings in the US." *Review of Income and Wealth* 60(4): 930-947.
Humphries, John Eric, Juanna Schrøter Joensen, and Gregory F. Veramendi. 2024. "The Gender Wage Gap: Skills, Sorting, and Returns." *AEA Papers and Proceedings* 114: 259-264.
Kirkebøen, Lars, Edwin Leuven, and Magne Mogstad, 2016. "Field of Study, Earnings, and Self-Selection," *The Quarterly Journal of Economics* 131(3): 1057-1111.

Kitagawa, Evelyn M. 1955. “Components of a Difference Between Two Rates.” *Journal of the American Statistical Association*, 50(272), 1168-1194.
Kospentaris, Ioannis and Leslie S. Stratton. 2021. “The Evolution of Labor Market Disparities Between Black, Hispanic, and White Men: 1968-2019.” Life Course Centre Working Paper 2021-08.
Kugler, Adriana D., Catherine H. Tinsley, and Olga Ukhaneva. 2021. “Choice of Majors: Are Women Really Different from Men?” *Economics of Education Review* 81: 102079.
Lepage, Louis-Pierre, Xiaomeng Li, and Basit Zafar. 2025. Anticipated Discrimination and Major Choice. NBER Working Paper 33680. April 2025.
Lovenheim, Michael and Jonathan Smith. 2023. “Returns to Different Postsecondary Investments: Institution Type, Academic Programs, and Credentials.” *Handbook of the Economics of Education* Vol 6: 187-318.
Machin, Stephen and Patrick A. Puhani. 2003. “Subject of Degree and the Gender Wage Differential: Evidence from the UK and Germany.” *Economics Letters* 79(3): 393-400.
McDonald, Judith A. and Robert J. Thornton. 2007. “Do New Male and Female College Graduates Receive Unequal Pay?" *Journal of Human Resources* 42(1): 32-48.
Neal, Derek A. and William R. Johnson. 1996. “The Role of Premarket Factors in Black-white Wage Differences.” *Journal of political Economy* 104(5): 869-895.
Oaxaca, Ronald. 1973. “Male-Female Wage Differentials in Urban Labor Markets.” *International Economic Review*, 14(3), 693-709.
Oster, Emily. 2019. “Unobservable Selection and Coefficient Stability: Theory and Evidence.” *Journal of Business & Economic Statistics* 37(2): 187-204.
Reber, Sarah, Michal Kurlaender, Iwunze Ugo, and Ember Smith. 2025. “Understanding Gender Gaps in College Enrollment: Evidence from California.” Mimeo.
Sakamoto, Arthur, Christopher R. Tamborini, and ChangHwan Kim. 2018. “Long-term Earnings Differentials Between African American and White Men by Educational Level.” *Population Research and Policy Review* 37: 91-116.
Saltiel, Fernando. 2023. “Multi-dimensional Skills and Gender Differences in Stem Majors.” *The Economic Journal* 133(651): 1217-1247.
Sloane, Carolyn M., Erik G. Hurst, and Dan A. Black. 2021. “College Majors, Occupations, and the Gender Wage Gap.” *Journal of Economic Perspectives* 35(4): 223-248.
Turner, Sarah E. and William G. Bowen. 1999. “Choice of Major: The Changing (Unchanging) Gender Gap.” *Industrial and Labor Relations Review* 52(2): 289-313.
Wiswall, Matthew and Basit Zafar. 2015. “Determinants of College Major Choice: Identification Using an Information Experiment.” *Review of Economic Studies* 82(2): 791-824.
Zafar, Basit. 2013. “College Major Choice and the Gender Gap.” *Journal of Human Resources* 48(3): 545-595.
Zhou, Xiang, and Guanghui Pan. 2023. “Higher Education and the Black-white Earnings Gap.” *American Sociological Review* 88(1): 154-188.

Table 1: Means of Analysis Variables

Variable	(1) Male	(2) Female	(3) White	(4) Black	(5) Hispanic	(6) Asian
Agriculture	0.046	0.023	0.048	0.008	0.010	0.003
Architecture	0.012	0.009	0.012	0.007	0.008	0.009
Biology & Health	0.060	0.118	0.080	0.108	0.101	0.178
Business	0.220	0.160	0.193	0.175	0.150	0.281
Communications	0.040	0.055	0.051	0.053	0.040	0.038
Comp Sci	0.029	0.004	0.015	0.013	0.011	0.034
Economics	0.016	0.004	0.010	0.004	0.005	0.025
Engineering	0.079	0.014	0.043	0.022	0.038	0.086
Interdisciplinary Studies	0.020	0.125	0.082	0.062	0.090	0.028
Liberal Arts	0.125	0.135	0.142	0.102	0.123	0.078
Science & Math	0.023	0.015	0.020	0.010	0.017	0.023
Social Science	0.074	0.141	0.112	0.128	0.107	0.093
Vocational	0.109	0.053	0.073	0.118	0.084	0.030
Undeclared	0.156	0.150	0.125	0.194	0.222	0.115
Double Major	0.007	0.008	0.007	0.004	0.006	0.021
Female	—	—	0.548	0.610	0.587	0.513
White	0.645	0.613	—	—	—	—
Black	0.087	0.107	—	—	—	—
Hispanic	0.207	0.230	—	—	—	—
Asian	0.058	0.048	—	—	—	—
Math Exam Score	0.647	0.487	0.679	0.062	0.371	0.808
	(0.670)	(0.709)	(0.608)	(0.821)	(0.746)	(0.607)
Reading Exam Score	0.504	0.521	0.627	0.191	0.346	0.472
	(0.602)	(0.581)	(0.497)	(0.710)	(0.655)	(0.684)
Top Ten Percent Math	0.287	0.207	0.281	0.084	0.167	0.392
	(0.452)	(0.405)	(0.449)	(0.277)	(0.373)	(0.489)
70th-90th Percentile Math	0.316	0.289	0.331	0.193	0.262	0.314
	(0.465)	(0.453)	(0.470)	(0.394)	(0.440)	(0.464)
Top Ten Percent Reading	0.251	0.259	0.307	0.116	0.171	0.264
	(0.434)	(0.438)	(0.461)	(0.321)	(0.376)	(0.441)
70th-90th Percentile Reading	0.303	0.301	0.328	0.224	0.264	0.290
	(0.459)	(0.459)	(0.470)	(0.417)	(0.441)	(0.454)
At Risk	0.174	0.17	0.109	0.312	0.292	0.155
	(0.379)	(0.376)	(0.312)	(0.463)	(0.454)	(0.362)
Limited English Profiency	0.005	0.005	0.000	0.001	0.017	0.022
	(0.071)	(0.073)	(0.016)	(0.031)	(0.130)	(0.148)
Economically Disadvantaged	0.149	0.173	0.036	0.297	0.463	0.184
	(0.356)	(0.376)	(0.187)	(0.457)	(0.499)	(0.388)
Earnings 6-10 Years Post-HS	8,351	7,543	8,365	6,693	7,080	8,004
	(7408)	(5840)	(6878)	(6504)	(5390)	(7115)
Earnings 11-15 Years Post-HS	14,283	10,595	13,024	9,787	10,610	14,208
	(13494)	(12647)	(14907)	(10165)	(8096)	(12239)
Earnings 16-20 Years Post-HS	20,476	13,521	17,962	12,539	13,783	20,934
	(22617)	(11797)	(19927)	(9538)	(12113)	(20946)
Observations	216,953	277,469	310,293	48,756	108,535	25,765

Notes: Standard Deviations in parentheses.

Table 2: Gender and Racial/Ethnic Differences in Earnings over Time

Earnings Period	(1) Male	(2) Female	(3) White	(4) Black	(5) Hispanic	(6) Asian
Earnings 6-10 Years Post-HS	8,351	7,543	8,365	6,693	7,080	8,004
		(808)		(1,673)	(1,285)	(361)
		10.7%		25.0%	18.1%	4.5%
Earnings 11-15 Years Post-HS	14,283	10,595	13,024	9,787	10,610	14,208
		(3,688)		(3,237)	(2,414)	(-1,184)
		34.8%		33.1%	22.7%	-8.3%
Earnings 16-20 Years Post-HS	20,476	13,521	17,962	12,539	13,783	20,934
		(6,954)		(5,423)	(4,179)	(-2,972)
		51.4%		43.2%	30.3%	-14.2%

Notes: The table displays mean earnings in each period from Table 1. The difference between male-female and between White and each racial/ethnic group is in parentheses, with the percent difference in earnings relative to the non-male/non-White mean shown in each third row.

Table 3: Male-Female Earnings Differences

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Earnings 6-10 Years Post-HS					
Male	808	588	573	176	203	201
	(201)	(153)	(133)	(83)	(84)	(62)
% Explained		27.2%	29.1%	78.2%	74.9%	75.1%
	Panel B: Earnings 11-15 Years Post-HS					
Male	3,688	3,228	3,180	2,545	2,569	2,410
	(349)	(270)	(244)	(190)	(198)	(184)
% Explained		12.5%	13.8%	31.0%	30.3%	34.7%
	Panel C: Earnings 16-20 Years Post-HS					
Male	6,954	6,142	6,062	5,254	5,299	5,013
	(555)	(434)	(409)	(365)	(379)	(362)
% Explained		11.7%	12.8%	24.4%	23.8%	27.9%
Controls + HS×Cohort FE		X	X	X	X	X
College×Cohort FE			X	X		
Major Group FE				X		
College×Major Group FE					X	X
CIP4 FE						X

Notes: Standard errors clustered at the institution-major level are in parentheses. % Explained is the percent of the raw earnings difference across groups explained by the covariates.

Table 4: Racial/Ethnic Earnings Differences

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	White-Black			White-Hispanic			White-Asian		
Panel A: Earnings 6-10 Years Post-HS									
White	1,673	442	508	1,285	36	13	361	709	1,201
	(250)	(93)	(85)	(242)	(55)	(53)	(404)	(194)	(125)
% Explained		73.6%	69.6%		97.2%	99.0%		-96.4%	-232.7%
Panel A: Earnings 11-15 Years Post-HS									
White	3,237	839	1,053	2,414	396	422	-1,184	-137	732
	(421)	(131)	(125)	(390)	(103)	(102)	(495)	(198)	(193)
% Explained		74.1%	67.5%		83.6%	82.5%		88.4%	161.8%
Panel A: Earnings 16-20 Years Post-HS									
White	5,423	1,309	1,656	4,179	971	1,061	-2,972	-1,041	268
	(634)	(194)	(181)	(578)	(177)	(168)	(832)	(436)	(428)
% Explained		75.9%	69.5%		76.8%	74.6%		65.0%	109.0%
Controls + HS×Cohort FE		X	X		X	X		X	X
College×Cohort FE		X	X		X	X		X	X
Major Group FE			X			X			X

Notes: Standard errors clustered at the institution-major level are in parentheses. % Explained is the percent of the raw earnings difference across groups explained by the covariates.

Table 5: Blinder-Oaxaca-Kitagawa Decompositions of Earnings Differences Due to Major Choice and Returns to Major Choice

Panel A: Male-Female

	Years after High School		
	6-10	11-15	16-20
Percent Explained by Major Choice	86.1%	26.0%	15.9%
Percent Explained by Major Returns	12.8%	19.7%	26.2%

Panel B: White-Black

	Years after High School		
	6-10	11-15	16-20
Percent Explained by Major Choice	16.2%	8.6%	4.5%
Percent Explained by Major Returns	30.4%	22.8%	26.8%

Panel C: White-Hispanic

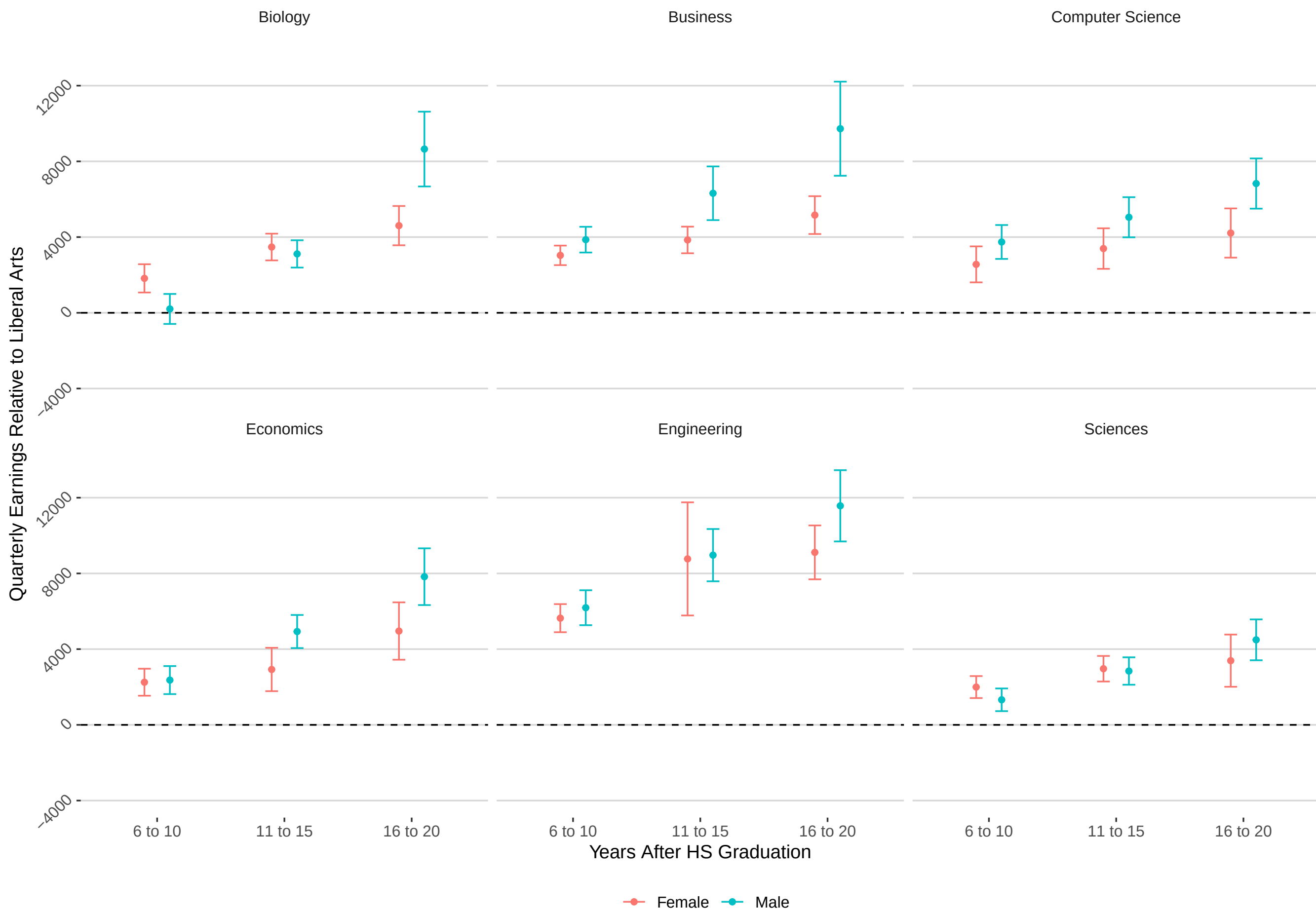
	Years after High School		
	6-10	11-15	16-20
Percent Explained by Major Choice	25.4%	16.4%	10.0%
Percent Explained by Major Returns	53.1%	36.7%	24.5%

Panel D: White-Asian

	Years after High School		
	6-10	11-15	16-20
Percent Explained by Major Choice	-176.6%	101.7%	63.1%
Percent Explained by Major Returns	43.3%	-41.6%	-46.3%

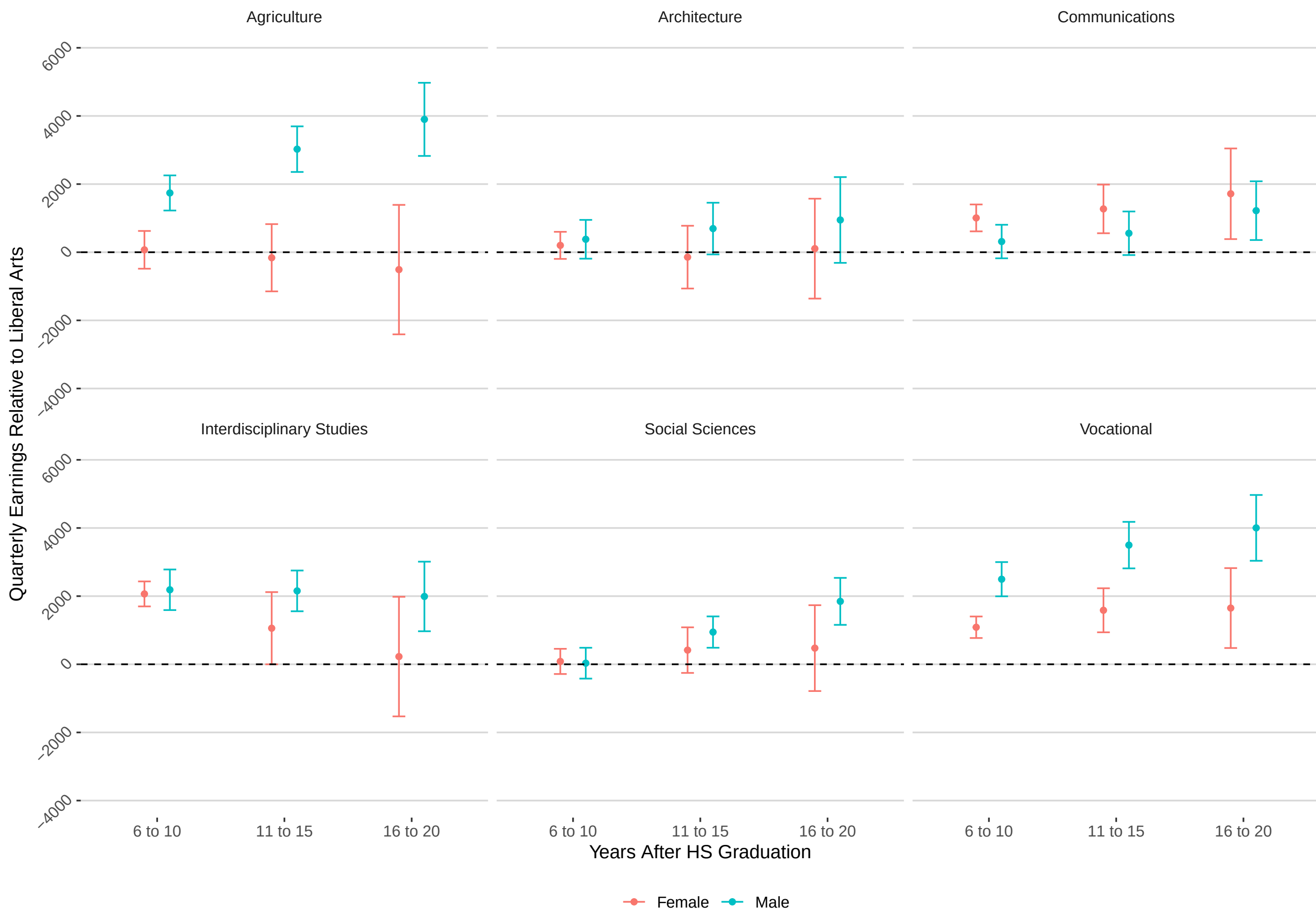
Notes: Percent Explained by Major Choice shows how much of the difference in earnings across groups would change if women (non-Whites) had the same distribution of majors as men (Whites). Percent Explained by Major Returns shows how much of the difference in earnings across groups would change if women (non-Whites) had the same returns relative to liberal arts as men (Whites).

Figure 1: Earnings Returns Over Time Relative to Liberal Arts, by Field and Gender – High Average Earnings Majors



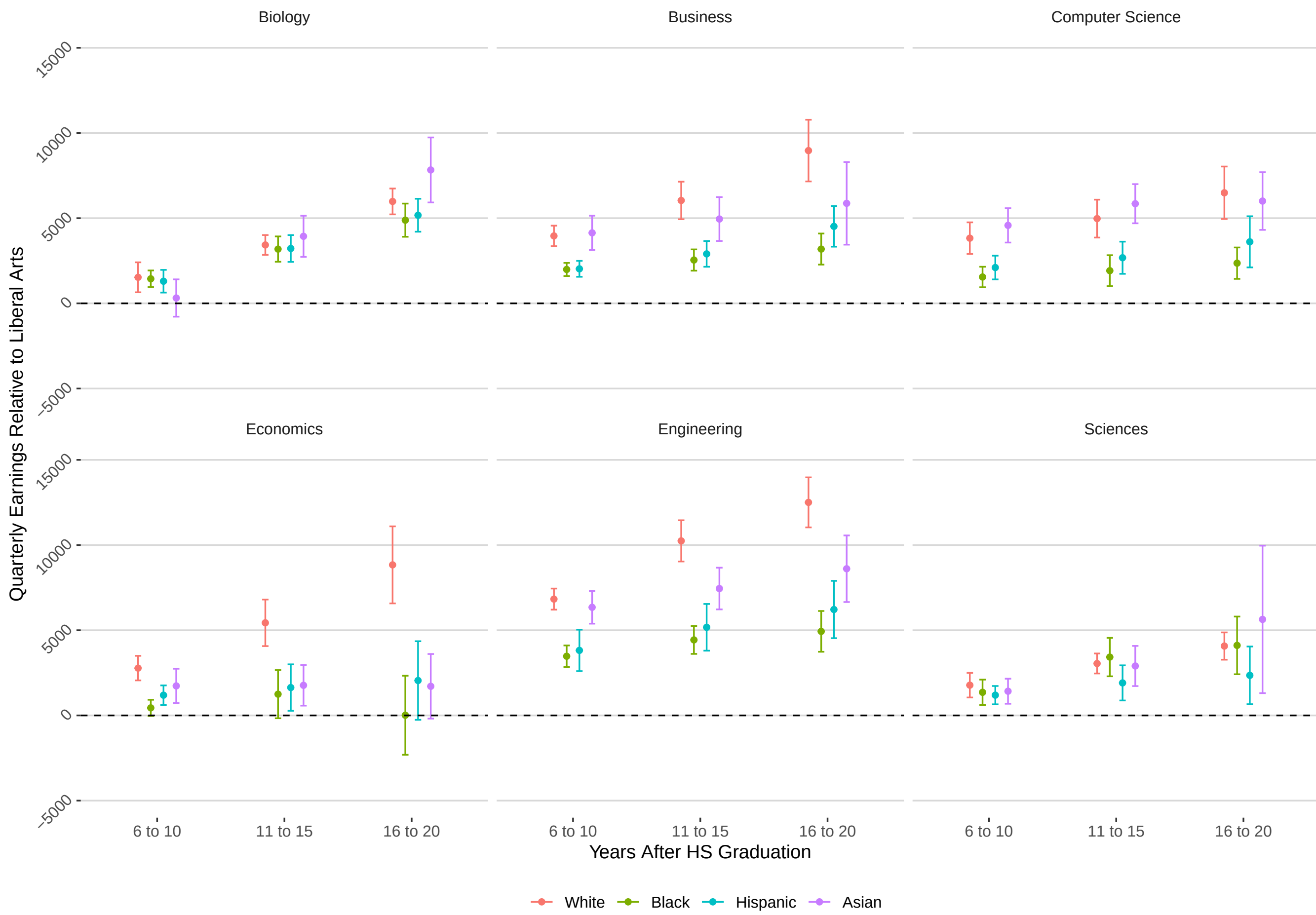
Notes: All estimates are relative to same gender liberal arts majors and include controls for high school test scores, student demographics, HS-by-cohort fixed effects, and college-by-cohort fixed effects. Outcomes are in dollars of quarterly earnings ($2016). Standard errors clustered at the institution-major level, and error bars represent the 95% confidence interval.

Figure 2: Earnings Returns Over Time Relative to Liberal Arts, by Field and Gender – Low Average Earnings Majors



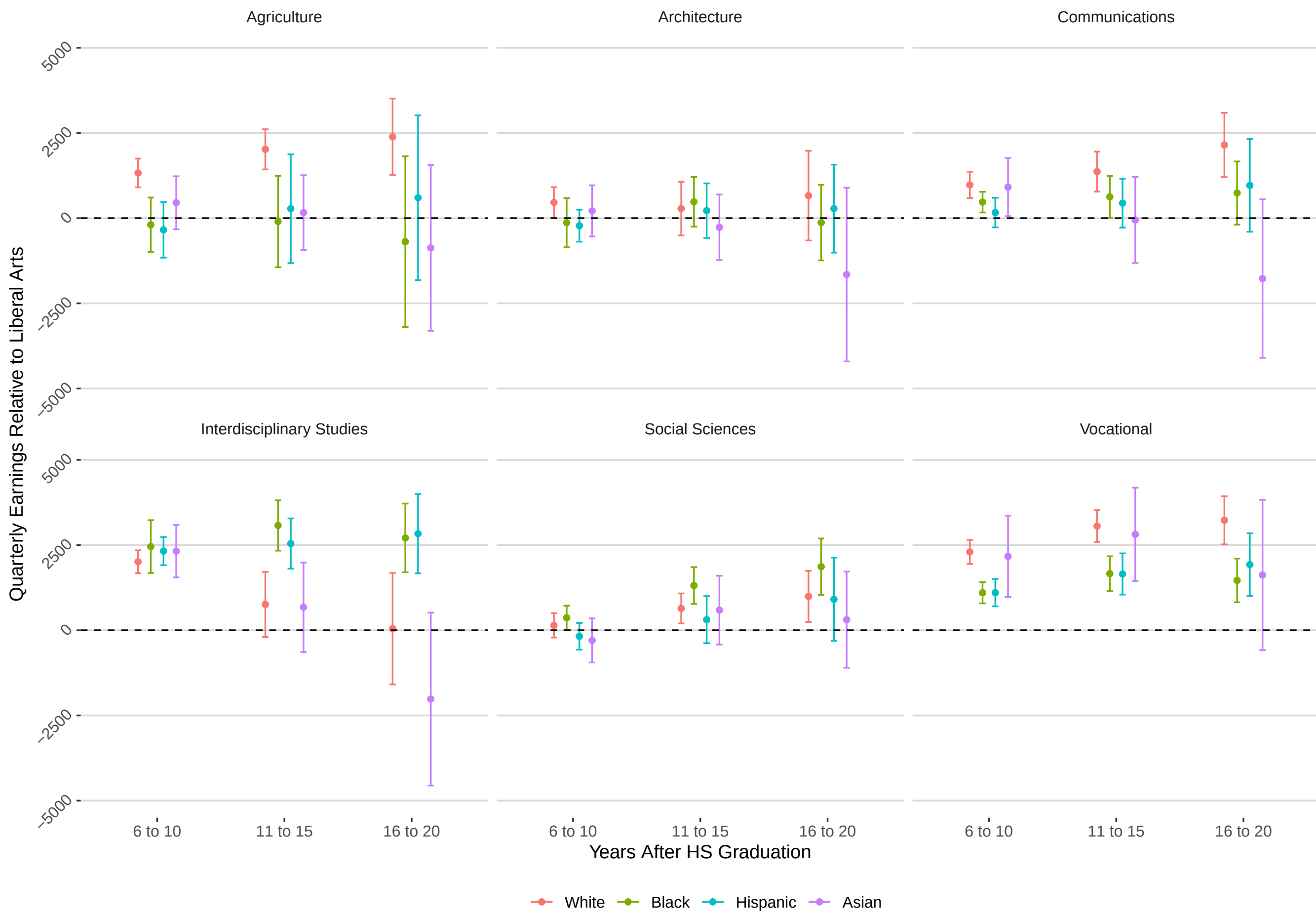
Notes: All estimates are relative to same gender liberal arts majors and include controls for high school test scores, student demographics, HS-by-cohort fixed effects, and college-by-cohort fixed effects. Outcomes are in dollars of quarterly earnings ($2016). Standard errors clustered at the institution-major level, and error bars represent the 95% confidence interval.

Figure 3: Earnings Returns Over Time Relative to Liberal Arts, by Field and Race – High Average Earnings Majors



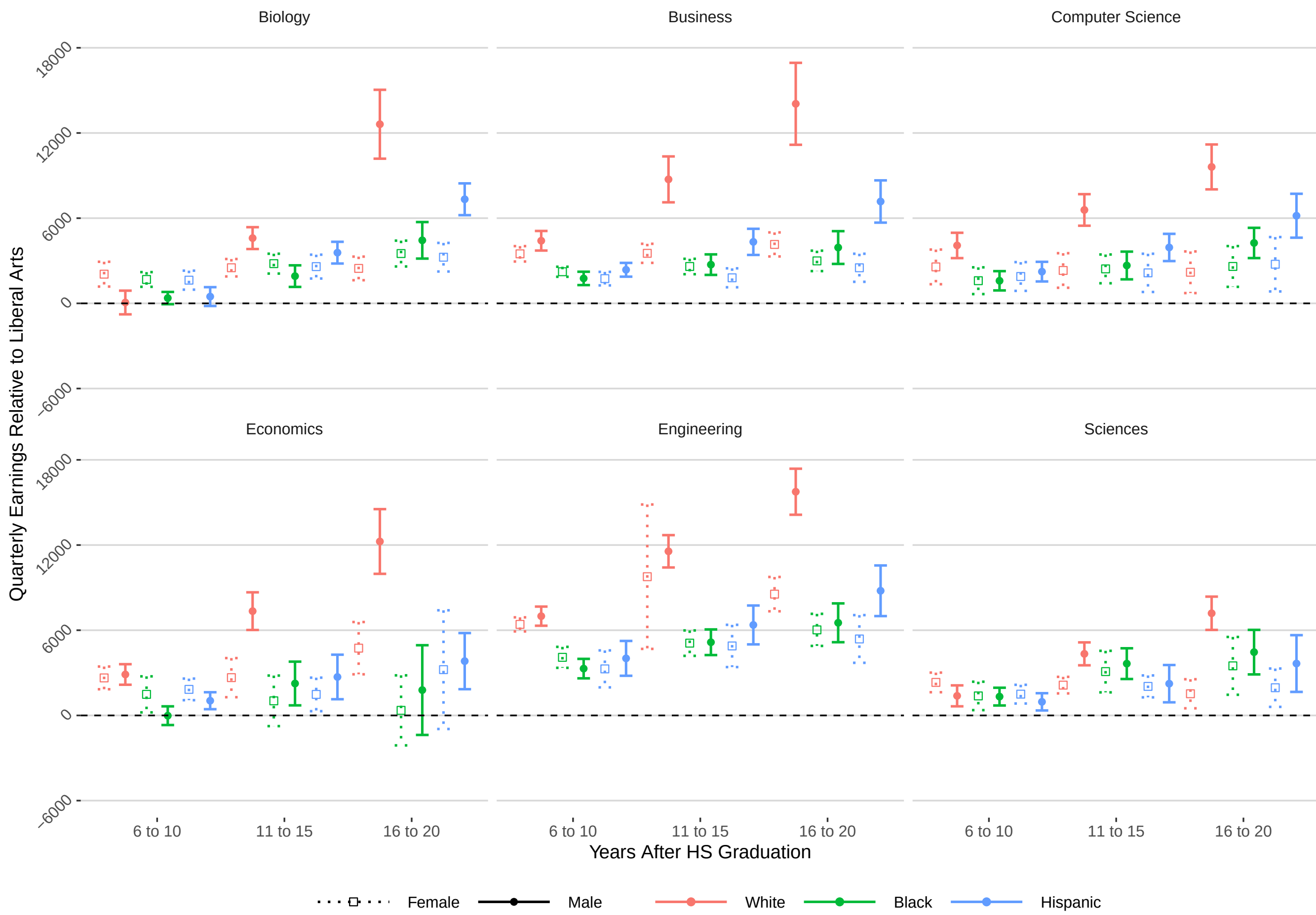
Notes: All estimates are relative to same race/ethnicity liberal arts majors and include controls for high school test scores, student demographics, HS-by-cohort fixed effects, and college-by-cohort fixed effects. Outcomes are in dollars of quarterly earnings ($2016). Standard errors clustered at the institution-major level, and error bars represent the 95% confidence interval.

Figure 4: Earnings Returns Over Time Relative to Liberal Arts, by Field and Race – Low Average Earnings Majors



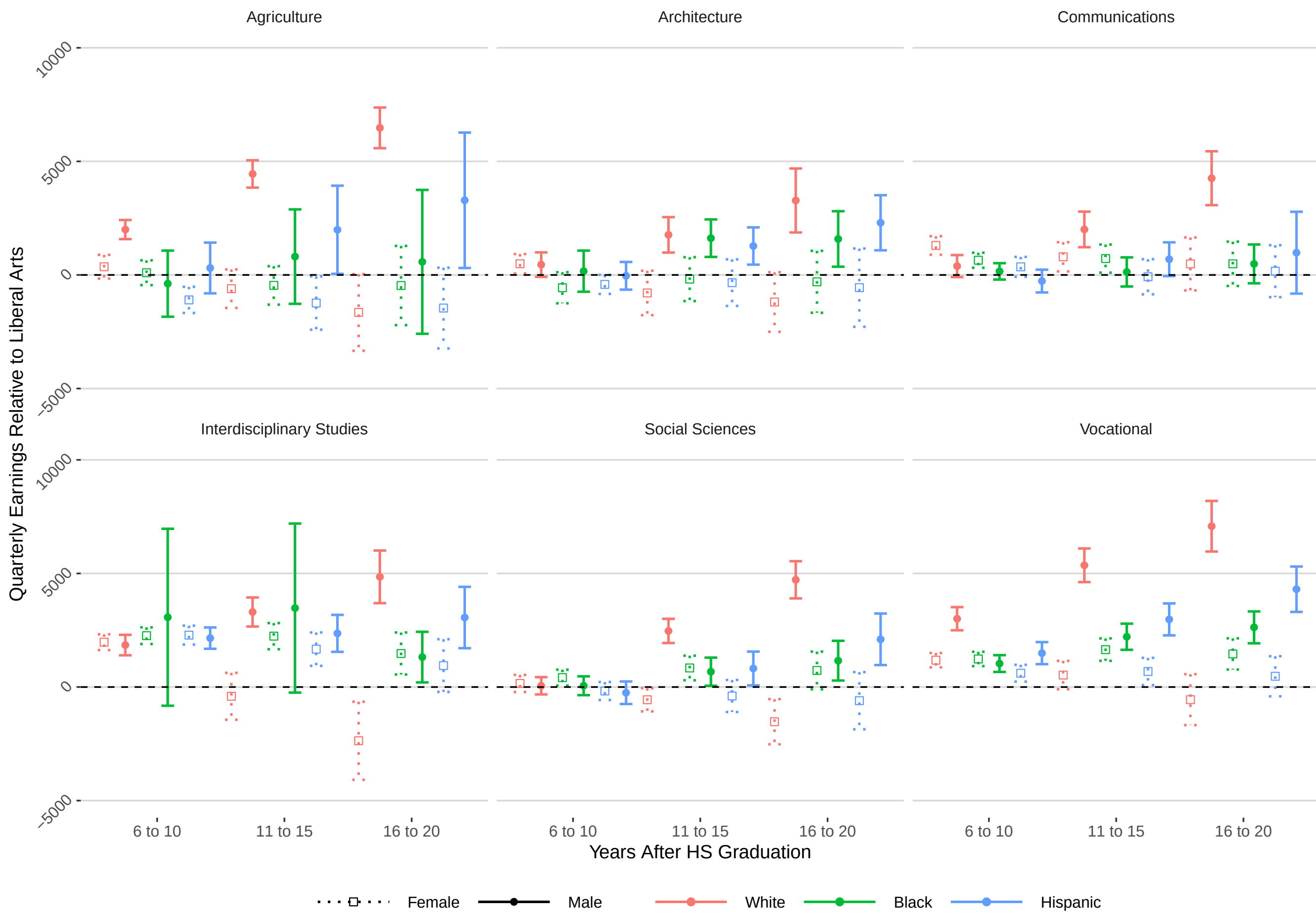
Notes: All estimates are relative to same race/ethnicity liberal arts majors and include controls for high school test scores, student demographics, HS-by-cohort fixed effects, and college-by-cohort fixed effects. Outcomes are in dollars of quarterly earnings ($2016). Standard errors clustered at the institution-major level, and error bars represent the 95% confidence interval.

Figure 5: Earnings Returns Over Time Relative to Liberal Arts, by Field and Gender x Race/Ethnicity – High Average Earnings Majors



Notes: All estimates are relative to same gender and race/ethnicity liberal arts majors and include controls for high school test scores, student demographics, HS-by-cohort fixed effects, and college-by-cohort fixed effects. Outcomes are in dollars of quarterly earnings ($2016). Standard errors clustered at the institution-major level, and error bars represent the 95% confidence interval.

Figure 6: Earnings Returns Over Time Relative to Liberal Arts, by Field and Gender x Race/Ethnicity – Low Average Earnings Majors

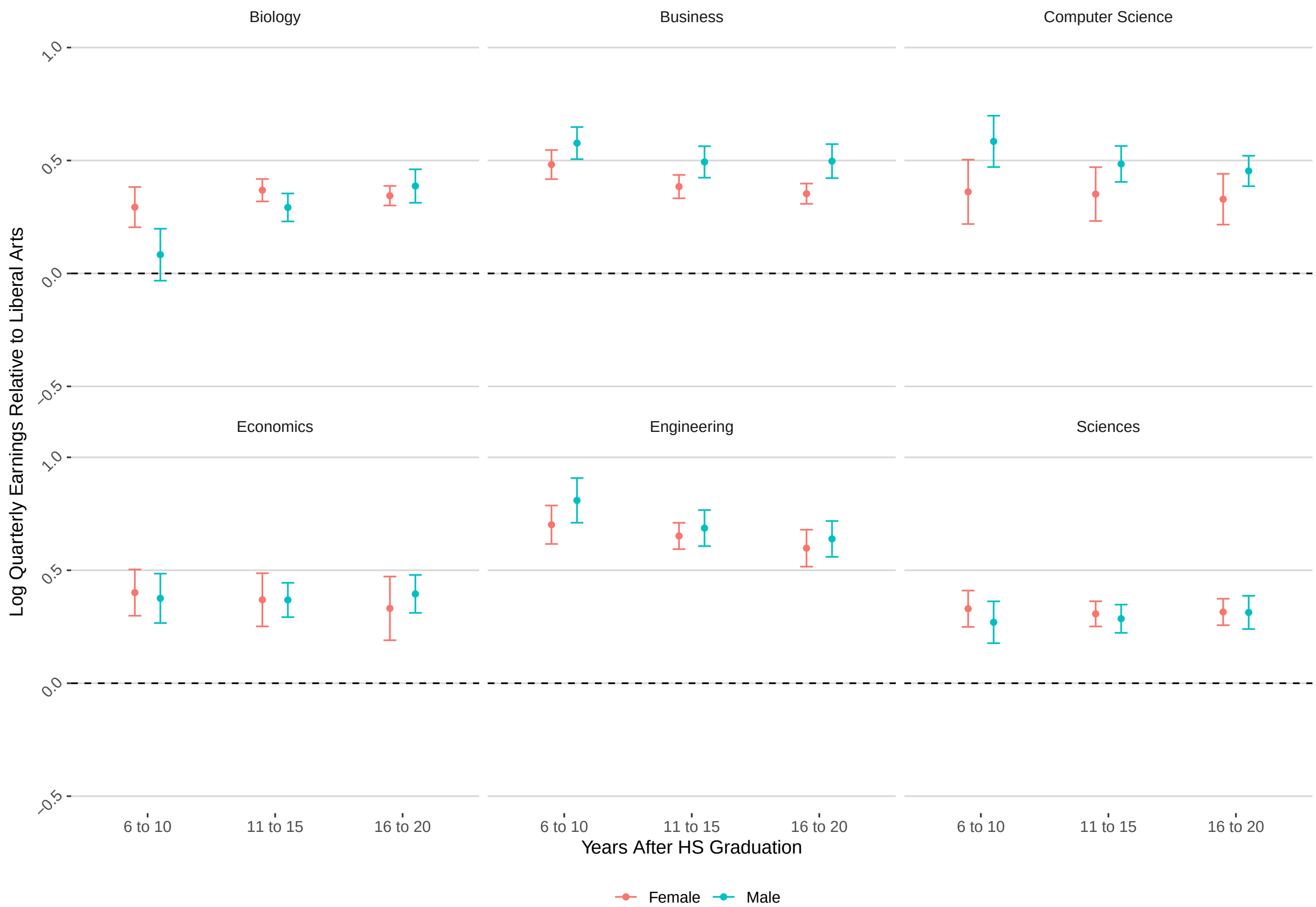


Notes: All estimates are relative to same gender and race/ethnicity liberal arts majors and include controls for high school test scores, student demographics, HS-by-cohort fixed effects, and college-by-cohort fixed effects. Outcomes are in dollars of quarterly earnings ($2016). Standard errors clustered at the institution-major level, and error bars represent the 95% confidence interval.

Online Appendix: Not for Publication

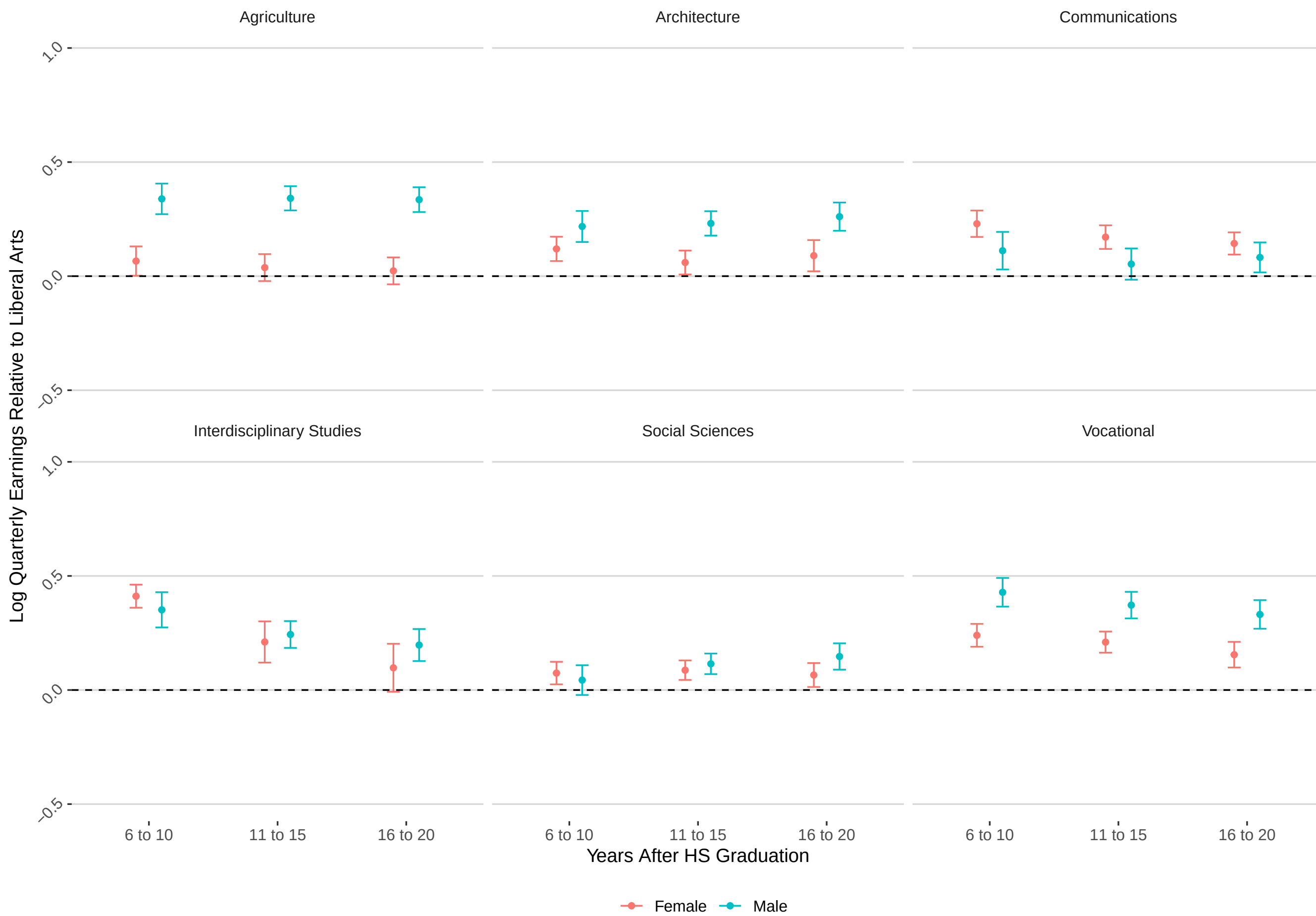
Appendix A: Supplemental Tables and Figures

Figure A-1: Log Earnings Returns Over Time, by Field and Gender – High Average Earnings Majors



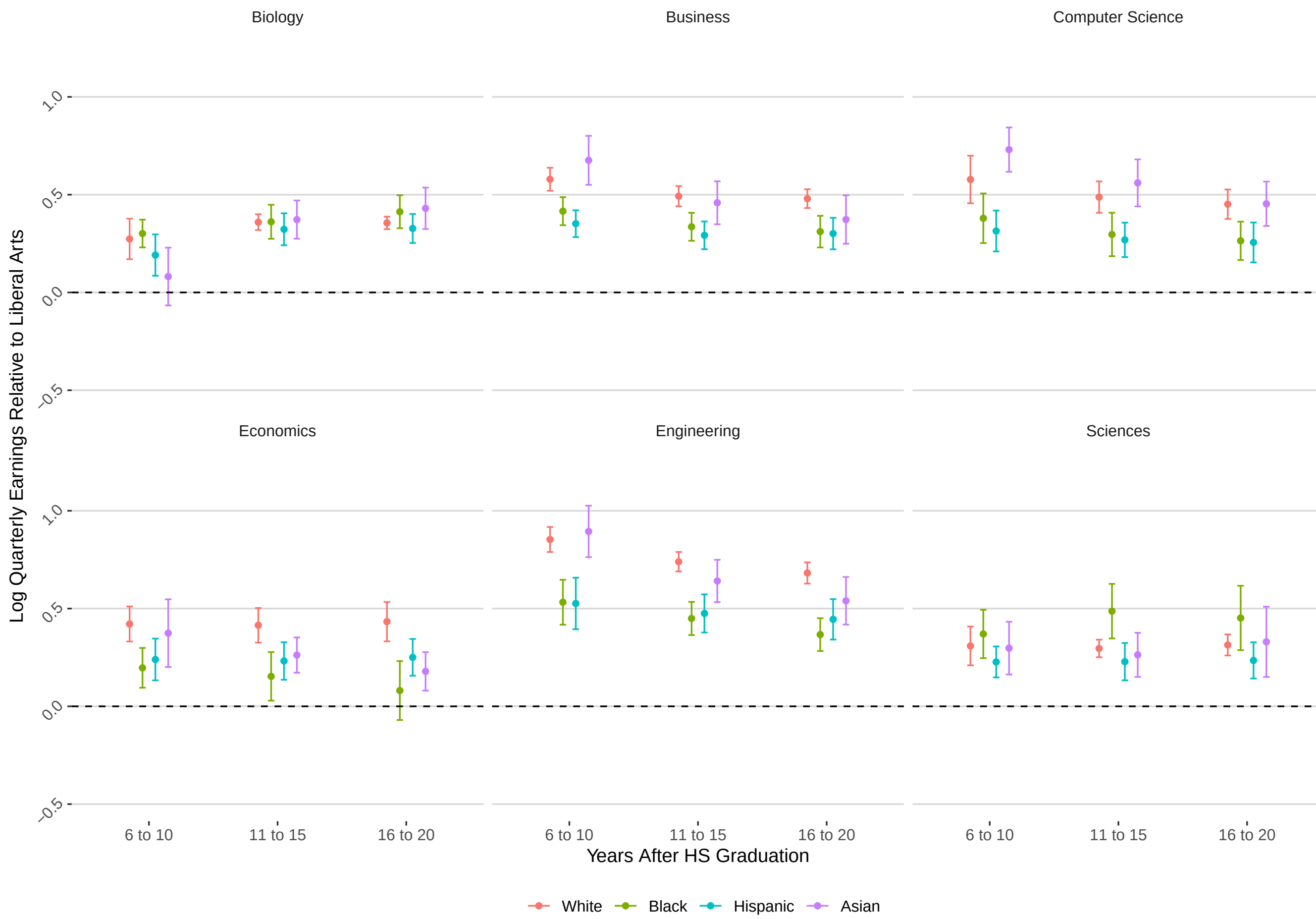
Notes: All estimates are relative to same gender liberal arts majors and include controls for high school test scores, student demographics, HS-by-cohort fixed effects, and college-by-cohort fixed effects. Outcomes are the natural log of dollars of quarterly earnings ($2016). Standard errors clustered at the institution-major level, and error bars represent the 95% confidence interval.

Figure A-2: Log Earnings Returns Over Time, by Field and Gender – Low Average Earnings Majors



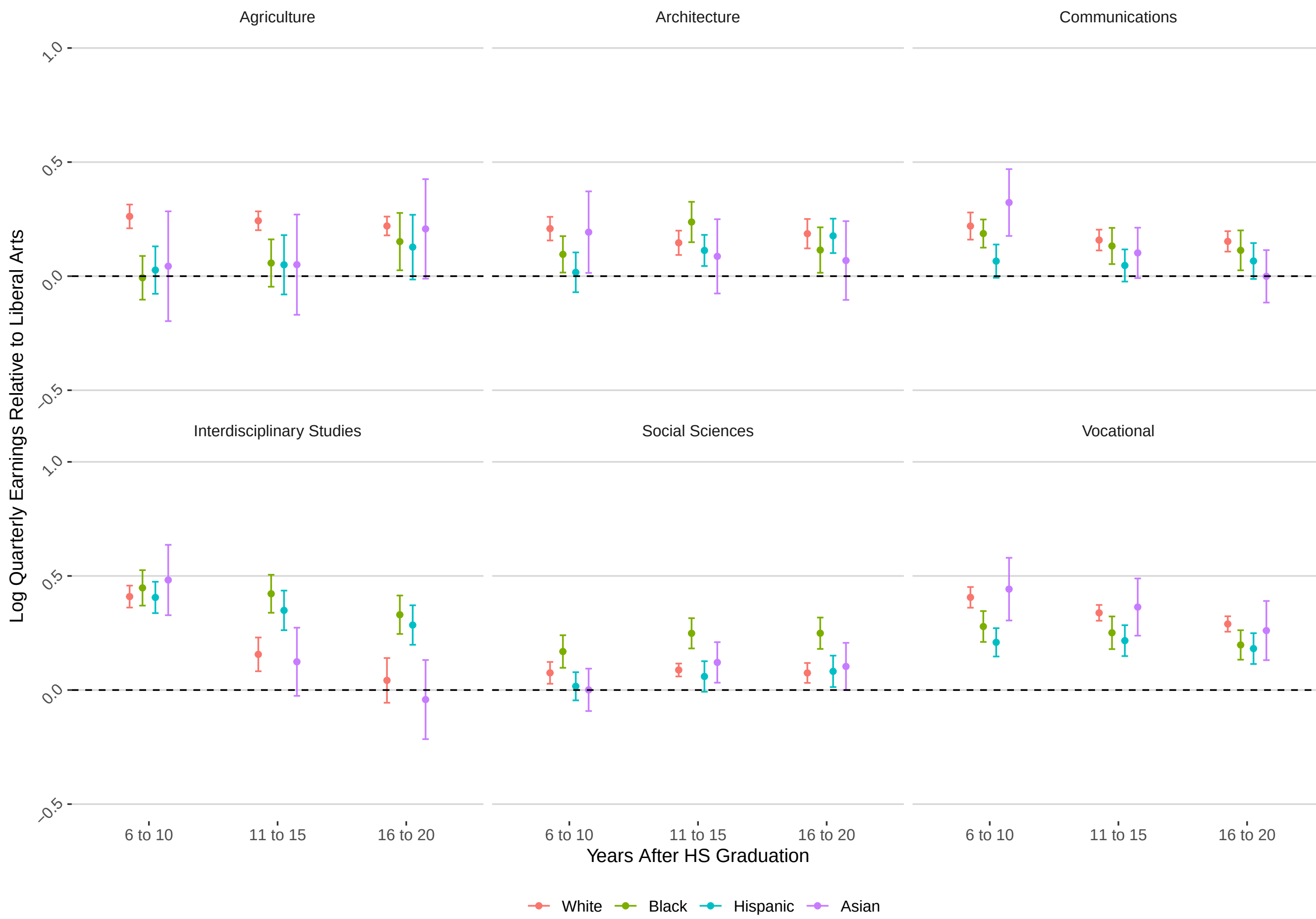
Notes: All estimates are relative to same gender liberal arts majors and include controls for high school test scores, student demographics, HS-by-cohort fixed effects, and college-by-cohort fixed effects. Outcomes are the natural log of dollars of quarterly earnings ($2016). Standard errors clustered at the institution-major level, and error bars represent the 95% confidence interval.

Figure A-3: Log Earnings Returns Over Time, by Field and Race – High Average Earnings Majors



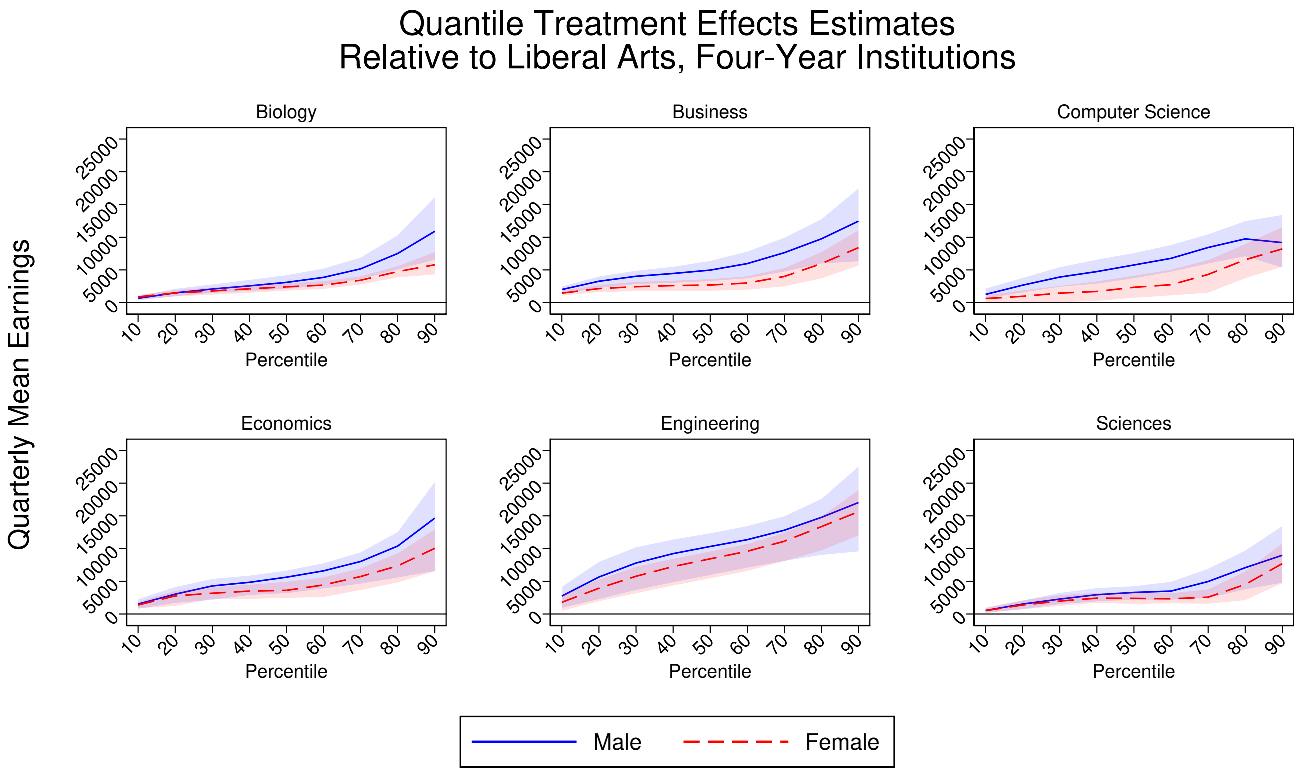
Notes: All estimates are relative to same race/ethnicity liberal arts majors and include controls for high school test scores, student demographics, HS-by-cohort fixed effects, and college-by-cohort fixed effects. Outcomes are the natural log of dollars of quarterly earnings ($2016). Standard errors clustered at the institution-major level, and error bars represent the 95% confidence interval.

Figure A-4: Log Earnings Returns Over Time, by Field and Race – Low Average Earnings Majors



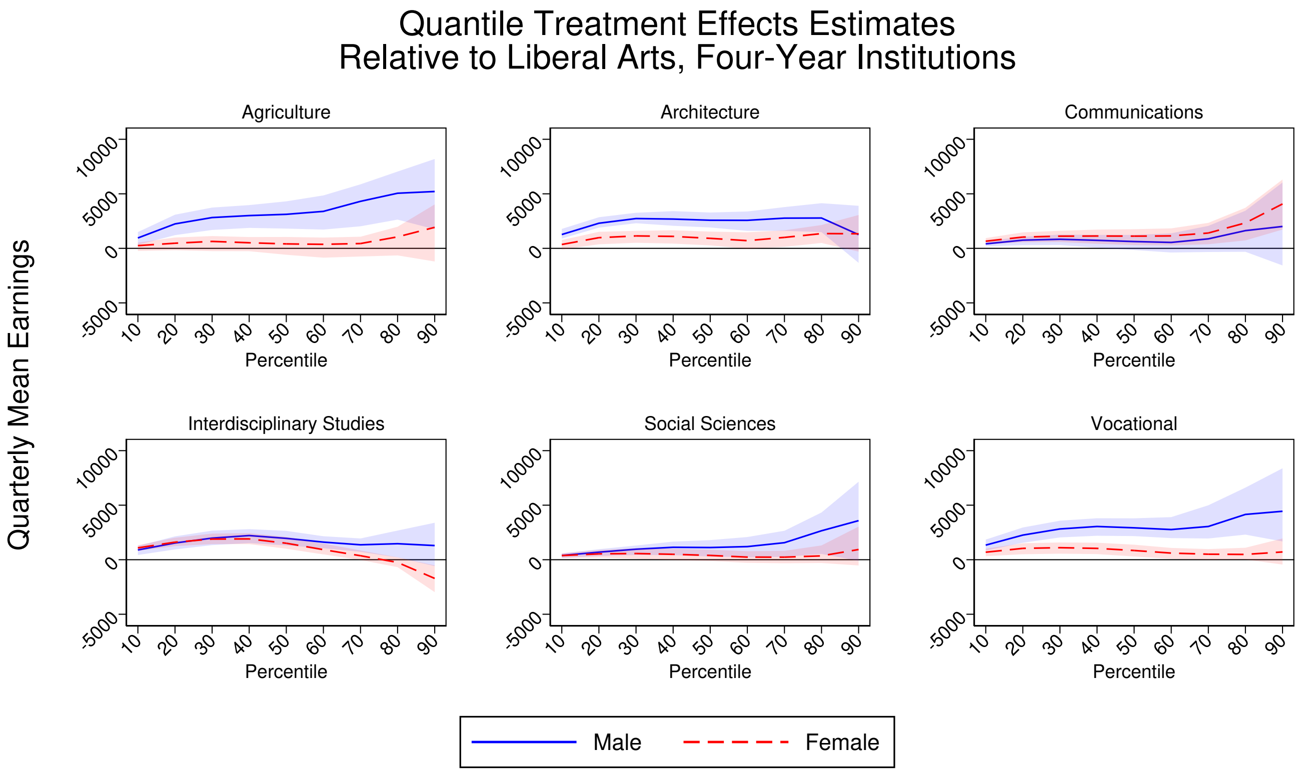
Notes: All estimates are relative to same race/ethnicity liberal arts majors and include controls for high school test scores, student demographics, HS-by-cohort fixed effects, and college-by-cohort fixed effects. Outcomes are the natural log of dollars of quarterly earnings ($2016). Standard errors clustered at the institution-major level, and error bars represent the 95% confidence interval.

Figure A-5: Quantile Treatment Effects, by Field and Gender – High Average Earnings Majors



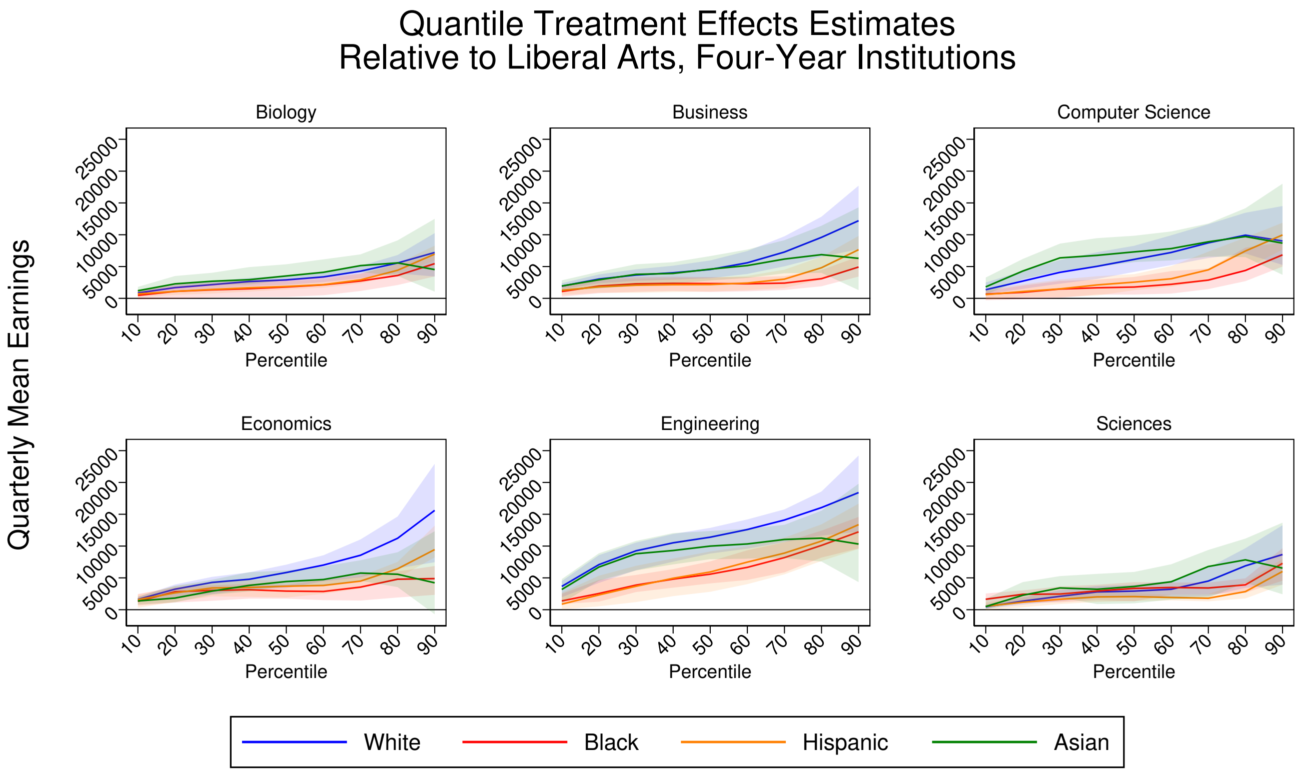
Notes: Figure shows quantile treatment effects for each major relative to same gender liberal arts majors. All estimates include controls for high school test scores, student demographics, HS-by-cohort fixed effects, and college-by-cohort fixed effects. Outcomes are in dollars of quarterly earnings ($2016). The solid curve shows quantile treatment effects for each decile from the 10^{th} to the 90^{th} percentile. The shaded region shows the 95% confidence interval, calculated using a block bootstrap at the institution-major level.

Figure A-6: Quantile Treatment Effects, by Field and Gender – Low Average Earnings Majors



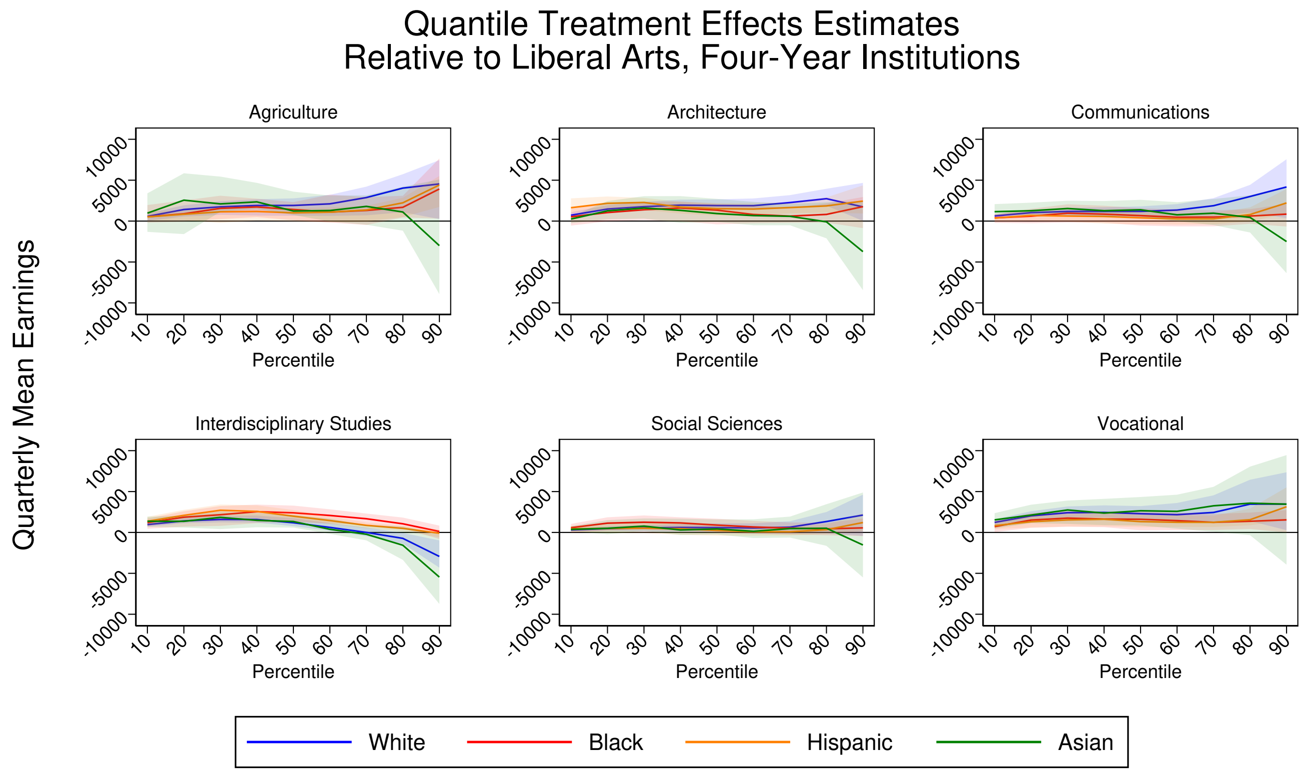
Notes: Figure shows quantile treatment effects for each major relative to same gender liberal arts majors. All estimates include controls for high school test scores, student demographics, HS-by-cohort fixed effects, and college-by-cohort fixed effects. Outcomes are in dollars of quarterly earnings ($2016). The solid curve shows quantile treatment effects for each decile from the 10^{th} to the 90^{th} percentile. The shaded region shows the 95% confidence interval, calculated using a block bootstrap at the institution-major level.

Figure A-7: Quantile Treatment Effects, by Field and Race – High Average Earnings Majors



Notes: Figure shows quantile treatment effects for each major relative to same race/ethnicity liberal arts majors. All estimates include controls for high school test scores, student demographics, HS-by-cohort fixed effects, and college-by-cohort fixed effects. Outcomes are in dollars of quarterly earnings ($2016). The solid curve shows quantile treatment effects for each decile from the 10^{th} to the 90^{th} percentile. The shaded region shows the 95% confidence interval, calculated using a block bootstrap at the institution-major level.

Figure A-8: Quantile Treatment Effects, by Field and Race – Low Average Earnings Majors



Notes: Figure shows quantile treatment effects for each major relative to race/ethnicity liberal arts majors. All estimates include controls for high school test scores, student demographics, HS-by-cohort fixed effects, and college-by-cohort fixed effects. Outcomes are in dollars of quarterly earnings ($2016). The solid curve shows quantile treatment effects for each decile from the 10^{th} to the 90^{th} percentile. The shaded region shows the 95% confidence interval, calculated using a block bootstrap at the institution-major level.

Table A-1: Gender and Racial/Ethnic Differences in Earnings over Time For Liberal Arts

Earnings Period	(1) Male	(2) Female	(3) White	(4) Black	(5) Hispanic	(6) Asian
Earnings 6-10 Years Post-HS	6,288	6,507	6,563	5,615	6,350	5,640
		219		(948)	(213)	(923)
		-3.4%		16.9%	3.4%	16.4%
Earnings 11-15 Years Post-HS	10,811	9,350	10,301	8,256	9,425	10,844
		(1,461)		(2045)	(877)	543
		15.6%		24.8%	9.3%	-5.0%
Earnings 16-20 Years Post-HS	15,280	12,075	14,133	10,612	11,782	17,626
		(3,205)		(3521)	(2351)	3493
		26.5%		33.2%	20.0%	-19.8%

Notes: The table displays mean earnings in each period for Liberal Arts majors. The difference between male-female and between White and each racial/ethnic group is in parentheses, with the percent difference in earnings relative to the non-male/non-White mean shown in each third row.

Table A-2: Male-Female Earnings Differences - Exclude Zero Earnings Periods

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Earnings 6-10 Years Post-HS					
Male	1,015	770	756	326	346	350
	(213)	(160)	(139)	(84)	(85)	(64)
% Explained		24.1%	25.5%	67.9%	65.9%	65.5%
	Panel B: Earnings 11-15 Years Post-HS					
Male	3,820	3,305	3,247	2,596	2,622	2,472
	(360)	(274)	(246)	(192)	(201)	(184)
% Explained		13.5%	15.0%	32.0%	31.4%	35.3%
	Panel C: Earnings 16-20 Years Post-HS					
Male	6,980	6,107	6,009	5,200	5,249	4,968
	(559)	(427)	(399)	(357)	(371)	(345)
% Explained		12.5%	13.9%	25.5%	24.8%	28.8%
Controls + HS FE		X	X	X	X	X
College FE			X	X		
Major Group FE				X		
College - Major Group FE					X	X
CIP4 FE						X

Notes: Standard errors clustered at the institution-major level are in parentheses. % Explained is the percent of the raw earnings difference across groups explained by the covariates.

Table A-3: Racial/Ethnic Earnings Differences, Additional Specifications

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	White-Black			White-Hispanic			White-Asian		
	Panel A: Earnings 6-10 Years Post-HS								
White	762	498	498	233	-5	-26	793	1,242	1,203
	(131)	(85)	(82)	(93)	(53)	(50)	(309)	(106)	(72)
% Explained	54.5%	70.2%	70.2%	81.9%	100.4%	102.0%	-119.7%	-244.0%	-233.2%
	Panel B: Earnings 11-15 Years Post-HS								
White	1,338	1,038	1,067	668	402	406	-228	842	1,005
	(200)	(130)	(132)	(157)	(101)	(100)	(322)	(234)	(237)
% Explained	58.7%	67.9%	67.0%	72.3%	83.3%	83.2%	80.7%	171.1%	184.9%
	Panel C: Earnings 16-20 Years Post-HS								
White	2,058	1,638	1,722	1,293	1,032	1,065	-1,451	537	1,011
	(286)	(188)	(192)	(239)	(165)	(166)	(557)	(489)	(490)
% Explained	62.1%	69.8%	68.2%	69.1%	75.3%	74.5%	51.2%	118.1%	134.0%
Controls + HS×Cohort FE	X	X	X	X	X	X	X	X	X
College×Cohort FE		X	X		X	X		X	X
College×Major FE		X			X			X	
CIP4 FE			X			X			X

Notes: Standard errors clustered at the institution-major level are in parentheses. % Explained is the percent of the raw earnings difference across groups explained by the covariates.

Table A-4: Racial/Ethnic Earnings Differences - Exclude Zero Earnings Periods

	(1)	(2)	(3)	(4)	(5)	(6)
I. White-Black						
Panel A: Earnings 6-10 Years Post-HS						
White	1,868	822	506	565	554	516
	(257)	(128)	(90)	(84)	(84)	(83)
% Explained		56.0%	72.9%	69.8%	70.3%	72.4%
Panel B: Earnings 11-15 Years Post-HS						
White	3,640	1,507	979	1,188	1,175	1,180
	(439)	(200)	(130)	(124)	(129)	(134)
% Explained		58.6%	73.1%	67.4%	67.7%	67.6%
Panel C: Earnings 16-20 Years Post-HS						
White	5,805	2,219	1,451	1,791	1,772	1,834
	(653)	(289)	(194)	(181)	(189)	(194)
% Explained		61.8%	75.0%	69.1%	69.5%	68.4%
II. White-Hispanic	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Earnings 6-10 Years Post-HS						
White	1,382	263	60	41	25	14
	(244)	(94)	(55)	(53)	(53)	(52)
% Explained		81.0%	95.7%	97.0%	98.2%	99.0%
Panel B: Earnings 11-15 Years Post-HS						
White	2,695	804	514	541	520	547
	(402)	(158)	(104)	(101)	(100)	(99)
% Explained		70.2%	80.9%	79.9%	80.7%	79.7%
Panel C: Earnings 16-20 Years Post-HS						
White	4,495	1,427	1,079	1,163	1,130	1,182
	(594)	(242)	(178)	(169)	(167)	(165)
% Explained		68.3%	76.0%	74.1%	74.9%	73.7%
III. White-Asian	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Earnings 6-10 Years Post-HS						
White	61	527	465	1,024	1,094	1,058
	(402)	(299)	(180)	(123)	(106)	(75)
% Explained		-764%	-662%	-1579%	-1693%	-1634%
Panel B: Earnings 11-15 Years Post-HS						
White	-1,417	-453	-326	571	681	818
	(532)	(344)	(203)	(194)	(224)	(235)
% Explained		68.0%	77.0%	140.3%	148.1%	157.7%
Panel C: Earnings 16-20 Years Post-HS						
White	-2,988	-1,483	-1,048	259	520	959
	(866)	(576)	(439)	(428)	(484)	(483)
% Explained		50.4%	64.9%	108.7%	117.4%	132.1%
Controls + HS FE		X	X	X	X	X
College FE			X	X		
Major Group FE				X		
College - Major Group FE					X	X
CIP4 FE						X

Notes: Standard errors clustered at the institution-major level are in parentheses. % Explained is the percent of the raw earnings difference across groups explained by the covariates.

Table A-5: The Effect of Major Choice on Earnings 6–10 Years Post-HS, by Gender and Race

Major	(1) Male	(2) Female	(3) White	(4) Black	(5) Hispanic	(6) Asian
Agriculture	1739.78	70.40	1326.436	-194.3399	-343.21	452.68
	(262.92)	(282.66)	(215.59)	(408.42)	(416.35)	(396.76)
Architecture	380.05	201.49	463.21	-131.54	-220.80	214.02
	(290.31)	(202.77)	(227.58)	(368.07)	(239.10)	(382.63)
Biology & Health	203.25	1819.56	1528.86	1441.29	1298.78	313.20
	(404.17)	(380.85)	(448.45)	(249.55)	(339.96)	(558.77)
Business	3864.47	3035.16	3957.82	1989.18	2026.23	4137.56
	(346.74)	(263.45)	(307.87)	(196.49)	(238.46)	(514.09)
Communications	313.77	1007.19	975.98	470.56	163.82	913.94
	(251.06)	(201.19)	(198.09)	(154.94)	(221.03)	(436.95)
Comp Sci	3741.73	2558.40	3826.26	1547.25	2101.89	4577.11
	(456.71)	(485.05)	(472.09)	(306.94)	(355.51)	(514.12)
Economics	2364.78	2252.17	2776.90	443.16	1187.95	1732.53
	(377.67)	(363.73)	(366.55)	(242.28)	(292.75)	(514.00)
Engineering	6188.15	5636.73	6828.12	3474.32	3817.20	6345.47
	(470.88)	(378.64)	(315.69)	(322.94)	(621.02)	(489.59)
Interdisciplinary	2186.44	2065.31	2009.51	2454.90	2321.91	2321.82
	(303.86)	(186.99)	(171.40)	(395.31)	(210.88)	(393.07)
Science & Math	1323.86	1996.14	1776.00	1356.71	1189.81	1420.54
	(305.81)	(296.39)	(366.02)	(380.40)	(274.34)	(375.22)
Social Science	32.32	84.23	142.76	366.59	-178.53	(299.06)
	(230.86)	(188.54)	(182.39)	(180.30)	(200.00)	(330.44)
Vocational	2496.89	1086.87	2297.11	1100.33	1103.87	2169.50
	(256.50)	(161.17)	(180.85)	(158.79)	(205.12)	(609.51)
Undeclared	-605.55	-1101.82	-1001.62	538.98	-1257.83	-104.92
	(230.38)	(178.99)	(178.16)	(167.09)	(214.18)	(290.40)

Notes: Columns (1) and (2) and columns (3)–(6) come from separate regressions of equation (2), using earnings 6–10 years after high school as the dependent variable. All estimates include controls for observed characteristics used in equation (2) as well as high school-by-cohort and college-by-cohort fixed effects. Liberal arts is the excluded category. Standard errors clustered at the institution-major level are shown in parentheses.

Table A-6: **The Effect of Major Choice on Earnings 11–15 Years Post-HS, by Gender and Race**

Major	(1) Male	(2) Female	(3) White	(4) Black	(5) Hispanic	(6) Asian
Agriculture	3024.95	-161.78	2020.344	-99.20612	278.90	165.07
	(341.45)	(503.65)	(300.73)	(684.87)	(814.09)	(559.38)
Architecture	694.10	(143.96)	280.77	479.36	220.95	(268.64)
	(387.00)	(469.82)	(402.00)	(371.57)	(407.95)	(490.57)
Biology & Health	3111.04	3474.66	3427.59	3184.67	3220.47	3935.17
	(368.16)	(360.07)	(297.19)	(379.44)	(401.56)	(615.66)
Business	6315.12	3848.37	6040.25	2543.12	2903.03	4949.18
	(723.63)	(358.52)	(562.15)	(318.57)	(385.43)	(656.74)
Communications	556.56	1271.35	1366.56	625.98	440.46	(54.21)
	(326.31)	(364.41)	(299.47)	(312.91)	(365.96)	(643.91)
Comp Sci	5047.68	3393.71	4973.76	1917.37	2677.35	5848.45
	(540.70)	(546.58)	(567.43)	(463.67)	(482.14)	(586.41)
Economics	4930.62	2925.56	5435.99	1247.33	1635.65	1767.11
	(446.02)	(584.58)	(697.28)	(721.09)	(695.59)	(609.10)
Engineering	8965.46	8767.88	10245.23	4432.61	5171.31	7447.60
	(704.33)	(1524.81)	(617.23)	(418.82)	(699.25)	(624.67)
Interdisciplinary	2154.27	1058.45	757.38	3074.26	2544.14	673.89
	(305.09)	(540.68)	(488.14)	(376.79)	(375.74)	(669.66)
Science & Math	2843.56	2965.22	3048.55	3423.97	1908.76	2901.67
	(369.41)	(344.56)	(299.39)	(575.86)	(526.09)	(601.35)
Social Science	945.06	415.63	640.23	1312.78	311.15	590.33
	(234.49)	(341.33)	(224.47)	(274.80)	(352.13)	(514.36)
Vocational	3497.56	1585.10	3057.72	1660.45	1650.60	2813.61
	(348.26)	(329.74)	(237.96)	(259.95)	(308.54)	(699.77)
Undeclared	-304.36	-343.61	-446.20	78.90	-855.32	495.23
	(280.07)	(319.74)	(269.69)	(354.95)	(317.60)	(458.54)

Notes: Columns (1) and (2) and columns (3)–(6) come from separate regressions of equation (2), using earnings 11–15 years after high school as the dependent variable. All estimates include controls for observed characteristics used in equation (2) as well as high school-by-cohort and college-by-cohort fixed effects. Liberal arts is the excluded category. Standard errors clustered at the institution-major level are shown in parentheses.

Table A-7: The Effect of Major Choice on Earnings 16-20 Years Post-HS, by Gender and Race

Major	(1) Male	(2) Female	(3) White	(4) Black	(5) Hispanic	(6) Asian
Agriculture	3899.57	-510.13	2389.964	-689.8698	598.99	-871.53
	(547.61)	(969.20)	(571.87)	(1278.30)	(1234.31)	(1240.95)
Architecture	946.66	105.60	661.43	-130.57	279.92	-1654.67
	(642.24)	(748.01)	(671.29)	(565.50)	(658.75)	(1300.58)
Biology & Health	8650.53	4604.83	5981.44	4882.01	5171.93	7829.69
	(1007.96)	(529.46)	(387.42)	(497.02)	(493.08)	(973.36)
Business	9726.12	5161.88	8966.32	3186.50	4516.95	5870.44
	(1268.01)	(509.64)	(923.57)	(465.69)	(607.18)	(1237.26)
Communications	1220.09	1715.71	2148.82	737.79	961.60	(1772.87)
	(439.80)	(678.58)	(481.45)	(473.00)	(694.07)	(1186.15)
Comp Sci	6828.57	4214.57	6490.40	2358.64	3610.93	6005.19
	(676.65)	(662.96)	(786.16)	(470.24)	(765.89)	(863.60)
Economics	7827.67	4956.21	8836.58	10.42	2048.31	1709.29
	(764.68)	(773.27)	(1153.81)	(1183.59)	(1176.81)	(967.95)
Engineering	11572.79	9111.94	12504.72	4933.25	6216.37	8609.61
	(960.22)	(726.08)	(748.88)	(610.53)	(858.42)	(997.80)
Interdisciplinary	1990.73	226.04	46.89	2709.80	2833.95	(2020.26)
	(521.05)	(895.43)	(834.82)	(514.12)	(593.49)	(1294.60)
Science & Math	4491.70	3390.93	4071.34	4110.01	2352.01	5636.06
	(550.77)	(703.42)	(408.37)	(864.12)	(863.88)	(2208.27)
Social Science	1846.54	474.70	992.07	1864.91	910.14	311.40
	(351.66)	(642.80)	(383.07)	(422.37)	(622.60)	(719.41)
Vocational	4003.39	1650.18	3226.62	1461.84	1925.86	1621.82
	(492.65)	(598.39)	(360.66)	(327.66)	(469.59)	(1125.46)
Undeclared	713.90	1229.07	769.59	-610.11	739.96	830.68
	(415.49)	(525.25)	(432.05)	(528.75)	(476.87)	(799.45)

Notes: Columns (1) and (2) and columns (3)-(6) come from separate regressions of equation (2), using earnings 16-20 years after high school as the dependent variable. All estimates include controls for observed characteristics used in equation (2) as well as high school-by-cohort and college-by-cohort fixed effects. Liberal arts is the excluded category. Standard errors clustered at the institution-major level are shown in parentheses.

Table A-8: Blinder-Oaxaca-Kitagawa Decompositions of Earnings Differences Due to Major Choice and Returns to Major Choice, Reversing the Base Group in the Decomposition

Panel A: Male-Female	Years after High School		
	6-10	11-15	16-20
Percent Explained by Major Choice	45.6%	18.1%	12.0%
Percent Explained by Major Returns	53.3%	27.6%	30.1%
Panel B: White-Black			
	6-10	11-15	16-20
Percent Explained by Major Choice	6.5%	2.0%	-0.8%
Percent Explained by Major Returns	40.1%	29.4%	32.1%
Panel C: White-Hispanic			
	6-10	11-15	16-20
Percent Explained by Major Choice	13.6%	7.0%	1.7%
Percent Explained by Major Returns	64.9%	46.0%	32.8%
Panel D: White-Asian			
	6-10	11-15	16-20
Percent Explained by Major Choice	-149.4%	93.6%	64.0%
Percent Explained by Major Returns	16.3%	-33.6%	-47.2%

Notes: Percent Explained by Major Choice shows how much of the difference in earnings across groups would change if men (non-Whites) had the same distribution of majors as men (Whites). Percent Explained by Major Returns shows how much of the difference in earnings across groups would change if women (non-Whites) had the same returns relative to liberal arts as men (Whites).

Table A-9: Blinder-Oaxaca-Kitagawa Decompositions of Earnings Differences Due to Major Choice and Returns to Major Choice - No Controls or Fixed Effects

Panel A: Male-Female			
	Years after High School		
	6-10	11-15	16-20
Percent Explained by Major Choice	97.4%	30.6%	19.9%
Percent Explained by Major Returns	16.9%	27.7%	33.4%
Panel B: White-Black			
	Years after High School		
	6-10	11-15	16-20
Percent Explained by Major Choice	20.0%	13.7%	10.0%
Percent Explained by Major Returns	19.6%	22.1%	25.2%
Panel C: White-Hispanic			
	Years after High School		
	6-10	11-15	16-20
Percent Explained by Major Choice	30.5%	23.9%	17.9%
Percent Explained by Major Returns	50.4%	37.7%	26.3%
Panel D: White-Asian			
	Years after High School		
	6-10	11-15	16-20
Percent Explained by Major Choice	-199.8%	124.1%	80.0%
Percent Explained by Major Returns	53.3%	-52.9%	-57.2%

Notes: Percent Explained by Major Choice shows how much of the difference in earnings across groups would change if women (non-Whites) had the same distribution of majors as men (Whites). Percent Explained by Major Returns shows how much of the difference in earnings across groups would change if women (non-Whites) had the same returns relative to liberal arts as men (Whites).

Table A-10: Blinder-Oaxaca-Kitagawa Decompositions of Earnings Differences Due to Major Choice and Returns to Major Choice - Controls but No Fixed Effects

Panel A: Male-Female			
	Years after High School		
	6-10	11-15	16-20
Percent Explained by Major Choice	90.7%	27.4%	16.8%
Percent Explained by Major Returns	18.1%	22.9%	28.9%

Panel B: White-Black			
	Years after High School		
	6-10	11-15	16-20
Percent Explained by Major Choice	18.5%	11.4%	0.1%
Percent Explained by Major Returns	24.2%	20.4%	22.3%

Panel C: White-Hispanic			
	Years after High School		
	6-10	11-15	16-20
Percent Explained by Major Choice	28.4%	20.3%	1.1%
Percent Explained by Major Returns	51.7%	34.8%	23.0%

Panel D: White-Asian			
	Years after High School		
	6-10	11-15	16-20
Percent Explained by Major Choice	-182.6%	106.8%	6.5%
Percent Explained by Major Returns	41.4%	-47.1%	-52.7%

Notes: Percent Explained by Major Choice shows how much of the difference in earnings across groups would change if women (non-Whites) had the same distribution of majors as men (Whites). Percent Explained by Major Returns shows how much of the difference in earnings across groups would change if women (non-Whites) had the same returns relative to liberal arts as men (Whites).

Table A-11: Earnings Differences 16-20 Years Post-HS Across Majors, Equalizing Occupation Choices Within Each Major

	Gender		White-Black		White-Hispanic		White-Asian	
Major	Difference	CF Difference	Difference	CF Difference	Difference	CF Difference	Difference	CF Difference
Agriculture	-186	-162	-887	233	-638	120	-605	132
Architecture	-639	31	7	310	1234	-17	1545	202
Biology & Health	5108	-864	661	787	518	867	-2994	523
Business	3385	291	4503	502	3574	443	3143	752
Communications	-567	-182	1338	144	256	51	-126	374
Comp Sci	2393	974	4567	729	3585	1007	-636	-96
Economics	6013	488	9423	1245	5267	628	4906	1122
Engineering	1026	111	4460	935	4920	988	-1088	3
Interdisciplinary Studies	-18	-8	-2146	-419	-1011	-167	-1737	-1002
Social Science	2604	584	707	217	163	104	-1368	-146
Science & Math	2436	88	3166	329	2007	771	601	-395
Vocational	1318	415	1540	90	445	-9	-4551	-1525

Notes: This table shows how earnings differences relative to liberal arts would change for each demographic group if occupation selection (at the SOC-2 level) were equalized across group within each major. “Difference” shows the raw difference in earnings 16-20 years post-high school between those in each major and liberal arts. “CF Difference” shows the earnings difference once we equalize the distribution of occupations across groups within each major. For example, the “CF Difference” shows how the earnings difference between Economics and Liberal Arts would change for men and women if female Economics majors had the same occupation distribution as men. These estimates are calculated using the American Community Survey (ACS) for cohorts likely to have graduated from high school between 1996 and 2002. Only those with a four-year degree have an identified college major in the ACS. We use a national sample of college graduates to maximize statistical power; all tabulations are constructed using individual sample weights. See Appendix B for more details.

Table A-12: The Effect of Major Choice on the Number of Positive Earnings Quarters, by Gender and Race

Major	(1) Male	(2) Female	(3) White	(4) Black	(5) Hispanic	(6) Asian
Agriculture	-3.85	-1.24	-2.31	-3.62	-5.46	-3.75
	(0.965)	(1.444)	(1.061)	(2.469)	(1.372)	(2.588)
Architecture	-4.04	-5.38	-4.70	-1.02	-4.35	-7.02
	(0.935)	(1.208)	(0.911)	(2.176)	(1.280)	(1.905)
Biology & Health	-6.05	-0.42	-2.20	-0.21	-3.07	-4.27
	(0.851)	(1.058)	(0.677)	(2.066)	(1.176)	(1.694)
Business	-0.31	0.79	0.41	1.26	-1.17	1.47
	(0.779)	(1.147)	(0.685)	(2.004)	(1.167)	(1.839)
Communications	-4.53	-2.49	-3.35	-2.58	-4.29	-3.16
	(1.041)	(1.071)	(0.721)	(2.047)	(1.228)	(1.619)
Comp Sci	-1.87	-1.88	-0.69	0.67	-3.55	2.36
	(0.851)	(1.318)	(0.918)	(2.285)	(1.536)	(1.680)
Economics	-2.36	0.64	-0.36	-0.12	-1.87	-1.03
	(0.841)	(1.295)	(1.052)	(2.102)	(1.205)	(1.594)
Engineering	-0.77	-1.24	0.96	-0.78	-3.66	2.19
	(0.875)	(1.295)	(0.799)	(2.242)	(1.566)	(1.673)
Interdisciplinary	-0.01	2.43	0.55	3.69	2.73	1.02
	(0.910)	(1.152)	(0.822)	(2.023)	(1.302)	(1.803)
Science & Math	-4.22	-0.13	-2.82	1.66	-2.06	-1.79
	(0.813)	(1.129)	(0.756)	(2.404)	(1.241)	(1.581)
Social Science	-5.85	-2.57	-4.44	-0.20	-4.26	-3.78
	(0.821)	(1.063)	(0.672)	(2.118)	(1.204)	(1.744)
Vocational	-0.81	0.26	0.65	1.07	-2.82	2.15
	(0.795)	(1.093)	(0.699)	(2.028)	(1.225)	(1.945)
Undeclared	-3.70	-1.48	-2.59	-0.84	-3.06	-2.80
	(0.839)	(1.112)	(0.700)	(2.153)	(1.209)	(1.722)
Constant	54.20	51.07	53.05	55.59	56.30	49.09
	(1.297)	(1.351)	(0.682)	(2.001)	(1.182)	(1.744)

Notes: Each column comes from a separate regression of the number of positive earnings quarters in the earnings sample on major choice, controlling for observed characteristics used in equation (1) as well as high school-by-cohort and college-by-cohort fixed effects. Liberal arts is the excluded category. Standard errors clustered at the institution-major level are shown in parentheses.

Table A-13: The Effect of Major Choice on Exiting the Earnings Sample, by Gender and Race

Major	Male	Female	White	Black	Hispanic	Asian
Agriculture	0.06	0.08	0.09	-0.01	0.10	0.04
	(0.017)	(0.017)	(0.018)	(0.050)	(0.030)	(0.045)
Architecture	0.11	0.10	0.12	-0.02	0.14	0.08
	(0.022)	(0.017)	(0.020)	(0.053)	(0.030)	(0.039)
Biology & Health	0.12	0.09	0.11	-0.05	0.11	0.09
	(0.017)	(0.015)	(0.021)	(0.051)	(0.029)	(0.026)
Business	0.01	-0.00	0.01	-0.08	0.02	-0.02
	(0.017)	(0.013)	(0.018)	(0.049)	(0.027)	(0.028)
Communications	0.06	0.06	0.07	-0.05	0.08	0.02
	(0.017)	(0.013)	(0.018)	(0.049)	(0.028)	(0.028)
Comp Sci	-0.01	0.01	-0.00	-0.10	0.01	-0.05
	(0.019)	(0.021)	(0.021)	(0.051)	(0.030)	(0.033)
Economics	0.05	0.04	0.07	-0.02	0.06	0.01
	(0.019)	(0.019)	(0.019)	(0.057)	(0.031)	(0.032)
Engineering	-0.00	0.01	0.01	-0.06	0.07	-0.05
	(0.018)	(0.017)	(0.020)	(0.052)	(0.030)	(0.029)
Interdisciplinary	0.02	-0.02	0.00	-0.12	-0.02	-0.02
	(0.020)	(0.014)	(0.019)	(0.048)	(0.033)	(0.036)
Science & Math	0.06	0.02	0.07	-0.07	0.05	-0.00
	(0.016)	(0.018)	(0.018)	(0.052)	(0.028)	(0.033)
Social Science	0.11	0.10	0.12	-0.03	0.10	0.09
	(0.018)	(0.013)	(0.019)	(0.048)	(0.026)	(0.027)
Vocational	0.01	0.06	0.05	-0.06	0.04	-0.01
	(0.016)	(0.013)	(0.018)	(0.048)	(0.027)	(0.029)
Undeclared	0.13	0.15	0.17	0.00	0.15	0.07
	(0.017)	(0.013)	(0.018)	(0.048)	(0.028)	(0.028)
Constant	0.66	0.68	0.62	0.79	0.63	0.73
	(0.029)	(0.026)	(0.018)	(0.048)	(0.027)	(0.028)

Notes: Each column comes from a separate linear probability model regression of whether an individual leaves the earnings sample on major choice, controlling for observed characteristics used in equation (1) as well as high school-by-cohort and college-by-cohort fixed effects. Liberal arts is the excluded category. Standard errors clustered at the institution-major level are shown in parentheses.

Table A-14: The Effect of Major Choice on Earnings 6-10 Years Post-HS Among BA Recipients, by Gender and Race

Major	(1) Male	(2) Female	(3) White	(4) Black	(5) Hispanic	(6) Asian
Agriculture	1730.21	-6.01	1245.47	-593.58	-838.72	667.60
	(276.22)	(289.31)	(226.27)	(412.48)	(299.41)	(562.07)
Architecture	373.84	172.35	433.20	-548.38	-390.67	512.94
	(295.14)	(230.74)	(252.63)	(395.44)	(245.38)	(447.90)
Biology & Health	-85.20	1797.57	1380.41	1514.52	1404.55	7.86
	(443.12)	(470.57)	(529.32)	(337.54)	(419.71)	(615.01)
Business	4244.47	3151.17	4117.01	2135.25	2078.26	4345.59
	(376.45)	(273.81)	(319.65)	(201.18)	(260.67)	(580.66)
Communications	323.29	906.77	941.48	160.90	47.66	907.77
	(260.29)	(223.30)	(215.03)	(198.73)	(234.29)	(547.28)
Comp Sci	5014.40	3711.57	4871.92	3126.15	3321.85	5288.65
	(445.77)	(612.64)	(482.30)	(385.63)	(529.41)	(560.69)
Economics	2507.41	2215.45	2786.71	188.87	1004.94	1938.15
	(419.33)	(387.83)	(384.59)	(353.29)	(341.77)	(635.88)
Engineering	7203.44	6029.53	7553.90	4454.23	4672.82	6738.58
	(344.73)	(346.76)	(254.50)	(361.75)	(575.88)	(541.56)
Interdisciplinary	2274.27	2087.92	2067.70	2123.91	2416.05	2401.82
	(273.36)	(202.64)	(188.20)	(213.81)	(209.02)	(489.65)
Science & Math	1644.18	2180.51	2025.56	1509.82	1435.48	1501.30
	(346.74)	(326.39)	(402.40)	(393.84)	(300.19)	(460.97)
Social Science	-18.35	-64.34	51.04	15.89	-400.44	-306.53
	(237.72)	(196.29)	(189.10)	(210.73)	(205.44)	(424.84)
Vocational	2744.76	997.28	2294.86	1043.05	1030.31	2193.25
	(300.47)	(170.06)	(209.92)	(184.86)	(231.28)	(693.69)
Mean % Difference:						
Overall		1.17		0.74	1.01	0.87
High Earning Majors		1.52		0.58	0.82	1.16

Notes: Columns (1) and (2) and columns (3)-(6) come from separate regressions of equation (2), using earnings 6-10 years after high school as the dependent variable. Only those who obtain a BA (graduate from a 4-year public institution in Texas) are included in the regressions. All estimates include controls for observed characteristics used in equation (2) as well as high school-by-cohort and college-by-cohort fixed effects. Liberal arts is the excluded category. Mean % Difference is the ratio of the male-female relative returns for each major for the completer sample relative to the overall sample in column (2) and the same ratio for the White-non-White difference in columns (4)-(6). We show this ratio for all majors (Overall) and for technical majors (Comp Sci, Engineering, Biology & Health, Science & Math, Business, and Economics). Standard errors clustered at the institution-major level are shown in parentheses.

Table A-15: The Effect of Major Choice on Earnings 11-15 Years Post-HS Among BA Recipients, by Gender and Race

Major	(1) Male	(2) Female	(3) White	(4) Black	(5) Hispanic	(6) Asian
Agriculture	3080.64	-187.62	1876.47	-803.07	-196.33	559.45
	(360.11)	(492.35)	(318.01)	(739.50)	(685.14)	(549.90)
Architecture	732.38	-100.81	271.94	-249.72	12.15	103.38
	(422.66)	(459.55)	(415.82)	(432.10)	(469.28)	(586.95)
Biology & Health	3463.70	3786.09	3702.38	3481.28	3721.48	3801.53
	(428.44)	(436.53)	(370.89)	(443.23)	(480.32)	(679.80)
Business	6897.00	4016.18	6224.74	2487.05	2952.41	5008.28
	(780.65)	(383.94)	(582.27)	(353.08)	(436.93)	(684.09)
Communications	655.35	1131.01	1358.39	-4.53	377.99	-134.74
	(344.94)	(391.43)	(312.78)	(422.82)	(418.12)	(716.86)
Comp Sci	6970.98	4693.39	6263.41	4067.93	4591.29	6659.03
	(547.84)	(651.11)	(576.39)	(571.22)	(787.23)	(604.91)
Economics	4965.53	2992.77	5131.15	808.47	1384.92	1786.74
	(555.73)	(580.40)	(760.19)	(712.55)	(658.76)	(711.92)
Engineering	10352.94	9532.89	11110.02	5686.55	6313.99	7643.35
	(515.65)	(1659.15)	(619.50)	(504.11)	(654.00)	(654.29)
Interdisciplinary	2142.67	903.36	745.78	2567.04	2599.78	749.38
	(339.12)	(580.24)	(524.09)	(419.74)	(396.11)	(741.09)
Science & Math	3548.52	3239.00	3497.05	3849.89	2235.39	2906.08
	(410.25)	(364.92)	(317.06)	(619.13)	(556.76)	(736.55)
Social Science	980.76	251.63	581.15	710.70	164.32	626.17
	(237.33)	(349.28)	(232.82)	(351.88)	(399.13)	(546.49)
Vocational	3830.46	1452.38	3004.52	1322.06	1531.13	2527.07
	(402.42)	(335.66)	(266.92)	(344.02)	(361.44)	(729.23)
Mean % Difference:						
Overall		1.04		0.69	1.22	0.92
High Earning Majors		1.00		0.93	0.79	1.32

Notes: Columns (1) and (2) and columns (3)-(6) come from separate regressions of equation (2), using earnings 11-15 years after high school as the dependent variable. Only those who obtain a BA (graduate from a 4-year public institution in Texas) are included in the regressions. All estimates include controls for observed characteristics used in equation (2) as well as high school-by-cohort and college-by-cohort fixed effects. Liberal arts is the excluded category. Mean % Difference is the ratio of the male-female relative returns for each major for the completer sample relative to the overall sample in column (2) and the same ratio for the White-non-White difference in columns (4)-(6). We show this ratio for all majors (Overall) and for technical majors (Comp Sci, Engineering, Biology & Health, Science & Math, Business, and Economics). Standard errors clustered at the institution-major level are shown in parentheses.

Table A-16: The Effect of Major Choice on Earnings 16-20 Years Post-HS Among BA Recipients, by Gender and Race

Major	(1) Male	(2) Female	(3) White	(4) Black	(5) Hispanic	(6) Asian
Agriculture	4018.66	-364.40	2179.22	-1318.02	96.16	155.70
	(630.05)	(951.49)	(612.13)	(1566.83)	(1220.91)	(1181.99)
Architecture	972.82	181.44	528.20	-908.98	-117.54	-1345.80
	(766.07)	(806.56)	(761.40)	(770.81)	(803.68)	(1504.50)
Biology & Health	10544.36	5216.19	6835.61	5739.24	6141.33	8224.60
	(1028.36)	(634.19)	(480.09)	(614.88)	(602.01)	(1067.87)
Business	10683.03	5525.70	9272.67	3180.68	4692.15	5860.25
	(1396.81)	(542.38)	(967.93)	(548.87)	(677.74)	(1246.44)
Communications	1393.25	1610.17	2178.39	254.64	930.08	-2104.06
	(543.78)	(731.34)	(543.57)	(670.87)	(781.03)	(1200.42)
Comp Sci	9197.51	5723.94	7862.15	4706.27	6107.16	6316.68
	(831.55)	(798.28)	(951.25)	(757.69)	(1177.62)	(815.82)
Economics	7991.85	5462.24	8443.47	-566.21	1707.64	1613.95
	(994.12)	(797.66)	(1277.77)	(1299.13)	(1143.90)	(1034.47)
Engineering	13339.63	9895.43	13311.46	6383.95	7523.93	8307.50
	(772.96)	(758.26)	(680.13)	(833.06)	(904.69)	(995.39)
Interdisciplinary	2275.31	67.17	192.86	2576.90	2989.09	-1847.17
	(629.51)	(955.70)	(900.64)	(681.23)	(675.00)	(1395.78)
Science & Math	5278.39	3723.52	4417.13	4464.29	2582.19	5797.82
	(714.61)	(735.70)	(499.34)	(1170.78)	(996.16)	(2438.14)
Social Science	2001.49	354.79	1027.86	1205.86	832.91	454.49
	(450.30)	(666.32)	(442.44)	(575.12)	(717.10)	(733.60)
Vocational	4308.09	1509.25	3039.83	1094.21	1460.55	1169.25
	(628.37)	(617.90)	(426.26)	(498.63)	(560.54)	(1149.78)
Mean % Difference:						
Overall		1.12		1.04	1.17	1.14
High Earning Majors		1.24		1.00	0.91	1.36

Notes: Columns (1) and (2) and columns (3)-(6) come from separate regressions of equation (2), using earnings 16-20 years after high school as the dependent variable. Only those who obtain a BA (graduate from a 4-year public institution in Texas) are included in the regressions. All estimates include controls for observed characteristics used in equation (2) as well as high school-by-cohort and college-by-cohort fixed effects. Liberal arts is the excluded category. Mean % Difference is the ratio of the male-female relative returns for each major for the completer sample relative to the overall sample in column (2) and the same ratio for the White-non-White difference in columns (4)-(6). We show this ratio for all majors (Overall) and for technical majors (Comp Sci, Engineering, Biology & Health, Science & Math, Business, and Economics). Standard errors clustered at the institution-major level are shown in parentheses.

Table A-17: Differences in GPA Relative to Liberal Arts by Demographic Group

Major	Male (1)	Female (2)	White (3)	Black (4)	Hispanic (5)	Asian (6)
Agriculture	-0.009	-0.083	-0.052	0.054	-0.121	-0.278
	(0.029)	(0.037)	(0.026)	(0.115)	(0.058)	(0.055)
Architecture	0.202	0.068	0.116	0.244	0.130	0.188
	(0.047)	(0.028)	(0.034)	(0.088)	(0.063)	(0.040)
Biology & Health	0.174	0.072	0.116	0.131	0.073	0.170
	(0.032)	(0.021)	(0.019)	(0.061)	(0.049)	(0.036)
Business	0.125	0.024	0.063	0.112	0.062	0.143
	(0.034)	(0.023)	(0.026)	(0.062)	(0.054)	(0.040)
Communications	0.106	0.031	0.045	0.181	0.073	0.011
	(0.032)	(0.021)	(0.025)	(0.060)	(0.051)	(0.028)
Comp Sci	-0.063	-0.077	-0.084	-0.180	-0.112	0.025
	(0.039)	(0.034)	(0.037)	(0.077)	(0.068)	(0.052)
Economics	-0.076	-0.150	-0.108	0.006	-0.053	-0.197
	(0.034)	(0.031)	(0.024)	(0.064)	(0.065)	(0.035)
Engineering	0.086	-0.019	0.057	0.067	-0.022	0.126
	(0.035)	(0.028)	(0.028)	(0.067)	(0.059)	(0.028)
Interdisciplinary	0.073	0.247	0.219	0.259	0.312	0.160
	(0.038)	(0.024)	(0.022)	(0.063)	(0.055)	(0.056)
Science & Math	0.076	0.025	0.029	0.146	0.075	0.062
	(0.033)	(0.033)	(0.026)	(0.092)	(0.057)	(0.052)
Social Science	0.075	0.034	0.038	0.178	0.058	-0.009
	(0.025)	(0.023)	(0.020)	(0.054)	(0.050)	(0.039)
Vocational	0.087	0.046	0.044	0.154	0.069	0.058
	(0.027)	(0.025)	(0.020)	(0.059)	(0.054)	(0.046)
Undeclared	-0.009	-0.035	-0.049	0.028	0.027	-0.118
	(0.038)	(0.029)	(0.028)	(0.085)	(0.057)	(0.038)

Notes: Each set of two columns comes from a separate regression of equation (2), using final GPA as the dependent variable. Final GPA is defined as the GPA at graduation or upon exiting the public 4-year sector in Texas. Each set of regressions controls for observed characteristics used in equation (2) as well as high school-by-cohort and college-by-cohort fixed effects. Uninteracted columns represent major effects on GPA for men (column 1) and Whites (columns 3, 5, 7). Liberal arts is the excluded category. Standard errors clustered at the institution-major level are shown in parentheses.

Table A-18: Blinder-Oaxaca-Kitagawa Decompositions of Earnings Differences Due to Major Choice and Returns to Major Choice Using CIP-4 Major Codes

Panel A: Male-Female			
	Years after High School		
	6-10	11-15	16-20
Earnings Gap	805	3685	6958
% Explained By CIP4 Choice	70.6%	27.4%	21.7%
% Explained By CIP4 Returns	25.8%	17.4%	19.5%
% Explained By Agg. Major Choice	85.1%	25.5%	15.6%
% Explained By Agg. Major Returns	12.6%	19.6%	25.9%

Panel B: White-Black			
	Years after High School		
	6-10	11-15	16-20
Earnings Gap	1606	3106	5273
% Explained By CIP4 Choice	16.9%	10.9%	8.1%
% Explained By CIP4 Returns	27.1%	18.2%	21.8%
% Explained By Agg. Major Choice	16.7%	8.2%	4.5%
% Explained By Agg. Major Returns	31.0%	22.8%	26.7%

Panel C: White-Hispanic			
	Years after High School		
	6-10	11-15	16-20
Earnings Gap	1279	2366	4115
% Explained By CIP4 Choice	29.1%	18.6%	12.0%
% Explained By CIP4 Returns	48.0%	34.0%	19.5%
% Explained By Agg. Major Choice	26.9%	17.5%	11.4%
% Explained By Agg. Major Returns	52.1%	37.3%	22.6%

Panel D: White-Asian			
	Years after High School		
	6-10	11-15	16-20
Earnings Gap	314	-1306	-3077
% Explained By CIP4 Choice	-185.9%	110.0%	83.4%
% Explained By CIP4 Returns	75.4%	-93.1%	-94.2%
% Explained By Agg. Major Choice	-200.3%	91.4%	60.0%
% Explained By Agg. Major Returns	71.5%	-65.9%	-63.6%

Notes: % Explained by CIP4 Choice shows how much of the difference in earnings across groups would change if women (non-Whites) had the same distribution of CIP4 majors as men (Whites). % Explained by CIP4 Returns shows how much of the difference in earnings across groups would change if women (non-Whites) had the same returns in each CIP4 major relative to liberal arts as men (Whites). % Explained by Agg. Major Choice and % Explained by Agg. Major Returns shows the same decompositions for the aggregate major categories used in our main analysis.

Table A-19: **Components of Aggregate Major Groups**

Aggregate Major Group	Specific Major	CIP Code
Agriculture + Natural Resources	Agriculture, Agriculture Operations, and Related Sciences	01, 02
	Natural Resources and Conservation	03
Architecture	Architecture and Related Services	04
Biology + Health	Biological and Biomedical Sciences	26
	Health Professions and Related Clinical Sciences	51
	Residency Programs	60
Business	Business, Management, Marketing, and Related Support Services	52, 08
Communications	Communication, Journalism, and Related Programs	09
Computer Science	Communications Technologies/Technicians and Support Services	10
	Computer and Information Sciences and Support Services	11
Economics	Economics	4506
Engineering	Engineering	14
Interdisciplinary Studies	Multi/Interdisciplinary Studies	3099
Liberal Arts	Area, Ethnic, Cultural, and Gender Studies	05
	Foreign Languages, Literatures, and Linguistics	16
	English Language and Literature/Letters	23
	Liberal Arts and Sciences, General Studies and Humanities	24
	Library Science	25
	Philosophy and Religious Studies	38
	Theology and Religious Vocations	39
	Visual and Performing Arts	50
	History	4508, 54
Vocational	Personal and Culinary Services	12
	Engineering Technologies/Technicians	15
	Vocational Home Economics	20
	Parks, Recreation, Leisure, and Fitness Studies	31
	Basic Skills	32
	Leisure and Recreational Activities	36
	Science Technologies/Technicians	41
	Security and Protective Services	43
	Construction Trades	46
	Mechanic and Repair Technologies/Technicians	47
	Precision Production	48
	Transportation and Materials Moving	49
	Reserve Officer Training Corps	28
	Military Technologies	29
	Citizenship Activities	33
	Health-Related Knowledge and Skills	34
	Interpersonal and Social Skills	35
	Personal Awareness and Self-Improvement	37
Physical Sciences + Math	Physical Sciences	40
	Mathematics and Statistics	27
Social Sciences	Family and Consumer Sciences/Human Sciences	19
	Legal Professions and Studies	22
	Psychology	42
	Public Administration and Social Service Professions	44
	Social Sciences, General	4501
	Anthropology	4502
	Archeology	4503
	Criminology	4504
	Demography and Population Studies	4505
	Geography and Cartography	4507
	International Relations and Affairs	4509
	Political Science and Government	4510
	Sociology	4511
	Urban Studies/Affairs	4512
	Sociology and Anthropology	4513
	Rural Sociology	4514
	Social Sciences, Other	4599
Undeclared		99

Appendix B: American Community Survey Analysis

We examine the role of occupation selection in cross-group earnings differences using the 2009-2023 American Community Survey (ACS). We align our analysis sample to match the ages and cohorts we use in the Texas data. We do not observe year of high school graduation, so we assume that individuals graduate high school at age 18. The high school graduating cohort is calculated as *Year-age+18*. We only keep observations that are in the 1996-2002 high school cohorts according to this calculation. The ages of those in our data span 24 to 38, so we then keep only respondents in the ACS between these ages. Field of study only is populated in the ACS for those with a 4-year degree. We keep in our analysis sample those who have at least a four-year degree and for whom there is non-missing major information, and we classify majors using the same classification scheme used throughout this analysis (see Online Appendix Table A-14). In order to match income in the ACS as closely as possible with quarterly earnings, we use the variable *incwage*, which contains each respondent's total pre-tax wage and salary income. As in the Texas data, we inflate all earnings to real 2016 dollars using the CPI-U. Wage and salary information in the ACS is annual, so we divide by 4 to convert to quarterly earnings. Those with zero earnings are included. Our final sample has 2,864,047 observations, and all tabulations and results employ individual sample weights to make them representative of the U.S. college graduate population.

We first estimate the analog in the ACS data to the return to college major. For each major, k and in each age range (6-10, 11-15, and 16-20 years post high school graduation), we calculate the difference between earnings in major k and earnings in liberal arts (la): $Return^k = earn^k - earn^{la}$. We calculate this earnings difference for each group (male (m), female (f), White (w), Black (b), Hispanic (h), Asian (a)) and each age range for each non-liberal arts major. We then calculate the difference in relative earnings differences across groups in each age range: $Return^{km} - Return^{kf}$, $Return^{kw} - Return^{kb}$,

$Return^{kw} - Return^{kh}$, $Return^{kw} - Return^{ka}$. The "Difference" columns in Online Appendix Tables A-5, B-2, and B-3 show these tabulations for our three age ranges.

Finally, we construct "CF Difference" as the difference in relative earnings that would occur if we equalized the distribution of occupations for men and women (for gender) and between Black and White, Hispanic and White, and Asian and White college graduates within each major. We measure occupations at the SOC-2 level, which includes 23 different occupations. We construct CF Difference using a linear decomposition that shows how the differences in relative returns across groups would change if the groups had the same distribution of occupations within each major.

We illustrate this decomposition below for the difference between males and females for major k. Let $Earn^{mk}$ be mean earnings for men in major k and $Earn^{wk}$ be earnings for women in major k. Earnings in each major can be written as a weighted average of earnings of those in each occupation:

$$Earn^{mk} = \sum_{o=1}^{23} P_o^{mk} Earn_o^{mk}$$
$$Earn^{wk} = \sum_{o=1}^{23} P_o^{wk} Earn_o^{wk}$$

where P_o^{mk} is the proportion of men from major k in occupation o. P_o^{wk} is similarly defined for women. We can decompose the difference in earnings by gender within major k as follows:

$$
\begin{aligned}
Earn^{mk} - Earn^{wk} &= \sum_{o=1}^{23} P_o^{mk} Earn_o^{mk} - \sum_{o=1}^{23} P_o^{wk} Earn_o^{wk} \\
&= \sum_{o=1}^{23} P_o^{mk} Earn_o^{mk} - \sum_{o=1}^{23} P_o^{wk} Earn_o^{wk} + \sum_{o=1}^{23} P_o^{mk} Earn_o^{wk} - \sum_{o=1}^{23} P_o^{mk} Earn_o^{wk} \\
&= \sum_{o=1}^{23} Earn_o^{wk} * (P_o^{mk} - P_o^{wk}) + P_o^{mk} * (Earn_o^{mk} - Earn_o^{wk})
\end{aligned}
$$

We only calculate the first part of this expression: $\sum_{o=1}^{23} Earn_o^{wk} * (P_o^{mk} - P_o^{wk})$, with the residual incorporating differences in earnings within occupation (and major) across men and women. We calculate "CF Difference" as the difference between the counterfactual earnings for major k minus the counterfactual earnings for liberal arts. This provides the differences in earnings across majors if men and women have the same distribution of occupations. We conduct similar calculations by race/ethnicity, using non-White earnings as the baseline.

Table B-1: Gender and Racial/Ethnic Differences in Earnings over Time

Earnings Period	(1) Male	(2) Female	(3) White	(4) Black	(5) Hispanic	(6) Asian
Earnings 6-10 Years Post-HS	10,867	8,869	9,957	8,385	8,565	10,623
		(1,998)		(1,572)	(1,392)	(666)
		22.5%		18.7%	16.3%	-6.3%
Earnings 11-15 Years Post-HS	16,164	11,772	14,062	11,244	11,684	15,676
		(4,391)		(2,817)	(2,378)	(1,614)
		37.3%		25.1%	20.4%	-10.3%
Earnings 16-20 Years Post-HS	21,309	13,806	17,728	13,671	14,319	20,190
		(7,503)		(4,057)	(3,409)	(2,462)
		54.3%		29.7%	23.8%	-12.2%

Notes: The table displays mean earnings in each period using the ACS sample as described in Appendix B. The difference between male-female and between White and each racial/ethnic group is in parentheses, with the percent difference in earnings relative to the non-male/non-White mean shown in each third row.

Table B-2: Earnings Differences 6-10 Years Post-HS Across Majors, Equalizing Occupation Choices Within Each Major

	Gender		White-Black		White-Hispanic		White-Asian	
Major	Difference	CF Difference	Difference	CF Difference	Difference	CF Difference	Difference	CF Difference
Agriculture	923.27	89.70	161.48	151.78	-242.39	-3.51	646.77	-46.16
Architecture	503.83	-3.18	-395.04	104.42	240.79	-51.93	828.58	-360.84
Biology & Health	-1005.65	-643.21	637.29	334.02	761.49	341.54	454.64	69.29
Business	1145.00	156.15	2133.28	277.34	1651.38	293.81	1157.94	148.40
Communications	-695.93	-235.54	671.08	113.91	680.85	-21.41	135.36	-48.60
Comp Sci	1848.13	927.48	2936.52	737.57	1871.91	913.38	-531.17	-627.10
Economics	1480.94	252.54	2535.60	609.46	2057.83	301.99	1796.04	493.55
Engineering	893.82	550.77	2558.48	876.96	2115.90	634.11	976.97	-529.64
Interdisciplinary Studies	177.19	-174.41	-118.66	-80.77	-219.28	14.28	163.88	-40.30
Science & Math	543.63	535.61	1521.66	389.66	784.85	354.58	903.18	-435.43
Social Science	566.71	247.42	57.81	9.71	150.90	-9.90	261.98	10.93
Vocational	1092.55	442.71	788.66	140.64	569.98	-17.23	-706.96	-1532.32

Notes: This table shows how earnings differences relative to liberal arts would change for each demographic group if occupation selection (at the SOC-2 level) were equalized across group within each major. "Difference" shows the raw difference in earnings 6-10 years post-high school between those in each major and liberal arts. "CF Difference" shows the earnings difference once we equalize the distribution of occupations across groups within each major. For example, the "CF Difference" shows how the earnings difference between Economics and Liberal Arts would change for men and women if female Economics majors had the same occupation distribution as men. These estimates are calculated using the American Community Survey (ACS) for cohorts likely to have graduated from high school between 1996 and 2002. Only those with a four-year degree have an identified college major in the ACS. We use a national sample of college graduates to maximize statistical power; all tabulations are constructed using individual sample weights. See Appendix B for more details.

Table B-3: Earnings Differences 11-15 Years Post-HS Across Majors, Equalizing Occupation Choices Within Each Major

	Gender		White-Black		White-Hispanic		White-Asian	
Major	Difference	CF Difference	Difference	CF Difference	Difference	CF Difference	Difference	CF Difference
Agriculture	10.42	-139.33	151.78	355.66	190.85	185.95	804.51	46.42
Architecture	-188.95	-59.01	1434.85	360.09	887.91	66.21	1091.93	306.28
Biology & Health	1014.97	-733.79	1073.28	595.31	792.15	553.56	-1159.34	241.15
Business	2361.62	171.43	3455.87	534.95	2487.79	362.50	2619.69	482.85
Communications	-665.23	-259.19	1349.66	200.86	929.01	40.21	-68.02	238.78
Comp Sci	2937.96	996.26	3787.48	906.62	2887.85	1034.01	-870.49	-470.80
Economics	2508.28	310.93	6111.86	911.76	4199.53	563.79	3116.42	843.95
Engineering	1213.97	356.78	3206.64	1014.19	2824.82	856.49	-678.44	-347.25
Interdisciplinary Studies	330.54	-143.13	-1192.65	-228.10	-627.39	-13.16	-837.84	-767.83
Science & Math	1587.37	293.04	2835.44	528.83	1763.39	518.31	652.13	-507.87
Social Science	1566.93	429.08	423.99	177.33	87.93	54.05	-523.56	-3.06
Vocational	1482.38	163.60	1615.22	303.11	708.82	17.78	-2445.51	-1563.10

Notes: This table shows how earnings differences relative to liberal arts would change for each demographic group if occupation selection (at the SOC-2 level) were equalized across group within each major. "Difference" shows the raw difference in earnings 11-15 years post-high school between those in each major and liberal arts. "CF Difference" shows the earnings difference once we equalize the distribution of occupations across groups within each major. For example, the "CF Difference" shows how the earnings difference between Economics and Liberal Arts would change for men and women if female Economics majors had the same occupation distribution as men. These estimates are calculated using the American Community Survey (ACS) for cohorts likely to have graduated from high school between 1996 and 2002. Only those with a four-year degree have an identified college major in the ACS. We use a national sample of college graduates to maximize statistical power; all tabulations are constructed using individual sample weights. See Appendix B for more details.