Online Appendix for "College Majors, Occupations, and the Gender Wage Gap" Not for Publication

Appendix Table of Contents by Section

A1 Data Description

Our primary data source is the American Community Survey (ACS). The ACS is conducted by the U.S. Census Bureau. The ACS samples roughly 1 percent of the U.S. population each year asking detailed questions on demographics, labor market variables and family structure. We downloaded the ACS samples from IPUMS USA database. For additional details, see Ruggles et al. (2019).

Given the possible impact of the Great Recession on undergraduate majors, we restrict our analysis to only include ACS respondents from the 2014-2017 surveys. Specifically, our base sample includes roughly 1.7 million observations of individuals aged 23 to 67 with a bachelor's degree who reported their undergraduate major. Of those with a bachelor's degree, 91.5 percent of ACS respondents between the ages of 23 and 67 reported at least one undergraduate major. The sample is restricted to include those who are not living in institutional group quarters, were born in one of the 50 U.S. states, have attained at least four years of college completion, and are age 23 to 67. We construct 5-year birth cohorts centered around the reported birth cohort. For example, the 1965 birth cohort includes those born between 1963 and 1967 (inclusive).

Starting in 2009, the ACS asked all respondents with a bachelor's degree to report their undergraduate major. For those respondents with a post-bachelor's degree, no additional information is provided for the field of study of their advanced degree(s). If individuals have more than one bachelor's degree or more than one major, they are prompted to list multiple majors. Approximately 11 percent of the observations in our sample have dual majors. Our analysis requires a maximum of one major for each unit of observation. Thus, we assign a primary major to each person based on the maximum median potential wage in the two majors (based on white men aged 43-57 as described above). This assignment process relies on the assumption that agents will present their highest-wage major as their primary major in the labor market.

We use the variables degfield, degfield2, degfielddd, and degfield2d in IPUMS to identify both broad and detailed majors. For the sample years 2014-2017, the ACS combines major responses into 176 distinct "detailed" majors. The ACS also aggregates these detailed majors into 29 "broad" major categories. Examples of the detailed majors include Journalism, Economics, Chemical Engineering, Molecular Biology, Music, and Finance while examples of the corresponding broad major fields include Communications, Social Sciences, Engineering, Biology/Life Sciences, Fine Arts, and Business. In our analysis, we aggregate to 134 detailed major categories by subsuming very small major categories into larger categories. For example, we combined General Agriculture, Soil Science, and Miscellaneous Agriculture into one detailed agricultural major. Similarly, we combine Mathematics, Actuarial Science, and Mathematics and Computer Science into one detailed mathematics major. Our main analysis uses these detailed major categories. We use the broad major categories to describe trends in Figure 1 and describe major-to-occupation mappings in Table 1 and Figure 6. Figures A1 to A5 include a full listing of our detailed and broad major codes. Our data replication kit provides the code for our combination of majors.

When data for key demographic variables are missing, the ACS imputes values including age, sex, race, place of birth, educational attainment and undergraduate major. In the 2014 to 2017 ACS, 276,448 (2.2 percent of the 2014-2017 ACS) respondents have imputed educational attainment information and 196,379 respondents (1.6 percent of the 2014-2017 ACS) have imputed degree field information. We restrict our sample to include only those with non-imputed age, sex, race, origin, educational attainment and undergraduate major field information. We use inverse probability weighting to correct for non-response. In doing so, we preserve the age, sex race, and state of birth joint distribution. In total, our analysis sample of ACS respondents includes 1,718,330 individuals.

Our analysis explores the independent contributions of educational and occupational specialization decisions to the college gender wage gap and explores gender differences in the mapping between undergraduate majors and occupation. For the 2014-2017 data, we use the reported occupation for all individuals in our sample with a valid, civilian occupation code who have worked within the previous five years. We use a balanced panel of detailed occupation codes based on the 1990 Occupation codes and following the cross-walking strategy outlined in Dorn (2009) and Autor and Dorn (2013), which construct a panel of 330 occupation codes. In our analysis, we aggregate to 251 detailed occupation codes by subsuming very small occupation categories into larger categories. For people who are employed, the ACS reports occupation based on primary occupation. For people who are unemployed, the ACS reports occupation based on their most recent primary occupation in the last five years.

In our analysis, we proxy an hourly wage by dividing reported annual labor income by the reported usual hours the respondent worked in the previous year times the reported number of weeks the respondent worked during the previous year. As the weeks worked variable is an intervaled variable in the 2014-2017 ACS, we assign the midpoint of the category as the number of weeks worked. Nominal wages are converted to real 2018$. In all analyses including wages, we follow the conventional practices in the literature and restrict the sample to a set of people with well-measured wages: those who are employed civilians (excluding the self-employed) with non-missing annual labor income and strong attachment to the labor market defined as usually working at least 30 hours a week for a minimum of 27 weeks in the previous year. In calculating the potential wage indices by occupation and undergraduate major, we restrict the sample to white men in their peak wage years (ages 45 to 55) with well-measured wages. All analyses use log wages.

A2 Construction of Potential Wage Indices

In Section , we define our potential wage index as:

$$I_c^{Major} = \frac{\sum_{m=1}^{M} s_{female,c}^{m} \bar{Y}_{male}^{m}}{\sum_{m=1}^{M} s_{male,c}^{m} \bar{Y}_{male}^{m}} - 1 \tag{4}$$

In practice, we compute this index by running the following regression locally within 5-year birth cohort c:

$$\bar{Y}_{male_i}^{m} = \alpha + \beta Female_i + \Gamma X_i + \epsilon_i \tag{5}$$

where $Female_i$ is a dummy variable indicating whether the respondent i has self-reported as female and X_i is a vector of demographic characteristics: race, state of birth, masters attainment, doctorate attainment, and marital status. Our potential wage index, I_c^{Major}, is defined as β from each local regression by 5-year birth cohort and therefore, measures the differential "potential" wage of women of cohort c given that the female distribution of major sorting in a given cohort may differ from males in their cohort. The units of this index are differential potential log wage based on major. In computing the comparable index for occupation, we substitute detailed occupation code, o, for detailed major code, m.

A3 A Detailed Analysis of Cross-Cohort Patterns in Occupational Mapping

Here, we delve further into the major-to-occupation mapping patterns discussed in Section . Appendix Figure A9 presents the results from this exercise. Specifically, we sort and segment the detailed group of 134 majors into deciles based on the potential wage of the major.[20] These bins are shown on the x-axis of Panel A of Appendix Figure A9. The top decile of majors (right-most bin along the x-axis) includes high earning majors like Economics, Chemical Engineering, Biochemical Sciences, Physics and Pharmacy. The bottom decile includes majors like Communications, Elementary Education, Theology, Counseling Psychology, and Drama and Theater Arts. Within each decile bin, we then compute the average potential wages based on occupation of individuals in the bin (shown on the y-axis of Panel A). We perform this analysis separately by gender and birth cohort.

[20]Recall, potential wages of a major are computed as the median log wage of native-born men between the ages of 43 and 57 who graduated with that major. Potential wages of an occupation are based on male native-born individuals between the ages of 43 and 57 who work in that occupation

Formally, the y-axis measures

$$\sum_{m=1}^{M}(s_{g,c}^{Occ}|d)\bar{Y}_{male}^{Occ} \tag{6}$$

where $s^Occ_{g,c}|d$ is the share of gender g choosing occupation Occ within major rank decile d and as previously $\bar{Y}_{male}^{Occ}$ measures the occupation conditional on major where occupations are measured by their potential male earnings.

Panel A of Appendix Figure A9 measures the extent to which the mapping patterns overall are concentrated within certain parts of the major pay distribution. The two top lines (that are dashed) show the mapping of majors to occupations for men from 1955 and 1975 five-year birth cohorts. The bottom two lines (that are solid) show the mapping of majors to occupations for women of the 1955 and 1975 five-year birth cohorts.

Panel B of Appendix Figure A9 shows the difference in the mapping between men and women for each of the two cohorts. If men and women systematically sort into different majors, they will be represented in different concentrations in the bins along the x-axis. Based on our findings in Section , we know this to be true: overall women sort into lower potential pay majors than men. Conditional of major rank, as men and women sort into different occupations, there will be variation in the mapping of majors to occupations within a given bin reflected as differences on the y-axis. If women are in lower-pay occupations conditional on major, the mapping of major (x-axis) to occupation (y-axis) will be systematically lower for women relative to men.

In fact, this is exactly what we see in Panel A of Figure A9. A few additional comments are worth highlighting from Panel A of Appendix Figure A9. First, both for men and women these series increase monotonically, reflecting stronger association between major and occupation within gender and that men and women in majors with higher potential wages generally select occupations with higher potential wages. For men, the mapping is nearly identical for older men (1955 cohort) as it is for younger men (1975 cohort). Remember, because in this calculation potential wages for both majors and occupations are based on the wages of U.S.-born, middle-aged, white men, deviation from monotonicity within the male series can only arise from race, cohort, or age effects within men.

For all cohorts of women, college women have sorted into occupations with systematically lower wages relative to their male counterparts conditional on the earnings potential of their undergraduate major. The gap is large. Occupations that women are in– conditional on major– have potential wages that are between 9 and 15 percent lower than occupations taken by men with the same majors.This has nothing to do with pay differences within an occupation, because we only use the within-occupation wages of U.S.-born, middle-aged, white men in this figure. All differences stem from women systematically sorting into lower pay occupations conditional on major.[21]

[21]There is a notable spike for both men and women in Bin 7 of Figure A9. This bin primarily includes Biology and Accounting majors that collectively comprise roughly 85 percent of individuals in this bin. The spike results from individuals in these majors disproportionately working in two very high potential wage occupations: Executive and Managerial occupations and Physician occupations. As seen in Appendix Figure A11, there is also a spike in Bin 7 with respect to potential hours worked which is consistent with the fact that the Executive and Managerial occupations and Physician occupations are driving this pattern.

Is cross-cohort convergence being driven by differential mapping patterns at different parts of the pay distribution? Panel B of Appendix Figure A9 helps us answer this question more directly by putting the information from Panel A in the form of differences (rather than levels) between men and women. We do this separately for the 1955 (triangles) and 1975 (x's) five-year birth cohorts. The vertical distance between the series confirms in the full set of majors and occupations the intuition established in the of broad majors in Figure 6: there is cross-cohort gender convergence in the mapping between majors and occupations.

Women in the 1975 cohort sorted into majors that were more similar to men and conditional on major worked in occupations that are more similar to their male peers than did college women from the 1955 birth cohort. This convergence is driven by women who majored in the highest potential pay majors. For the highest wage majors (deciles 9 and 10), women from the 1955 birth cohort worked in occupations that had log wages that were 12 percent lower than comparable men. Women in these majors from the 1975 cohort now only find themselves in occupations that have log wages that were 6 percent lower than men.

A4 Hours Differences Across Occupations

There is a large literature highlighting the fact that women work in occupations with lower annual hours worked relative to men. In this section, we explore this idea in the context of our methodology. To guide our empirical work, we define the following two variables: $\bar{H}^m_{male}$ and $\bar{H}^o_{male}$. $\bar{H}^m_{male}$ is defined as the median log annual hours worked for native-born white men between the ages of 43 and 57 who graduated with major m (regardless of subsequent occupation in which they worked). This is the potential hours associated with a given major based on older male hours. $\bar{H}^o_{male}$ is defined as the median log annual hours worked for native-born, white men between the ages of 43 and 57 who currently work in occupation o (regardless of undergraduate major). This is the potential hours associated with a given occupation based on older male hours. We refer to these variables as our potential annual hours worked indices. Majors (occupations) where men work more on average will have higher levels of $\bar{H}^m_{male}$ ($\bar{H}^o_{male}$).

How similar are men and women with respect to their occupations based on potential annual hours worked? Appendix Figure A8 displays $I^{H,Major}_c$ and $I^{H,Occ}_c$ for different cohorts. $I^{H,Major}_c$ is our potential hours index based on male annual hours worked in different majors and is defined as $I^{H,Major}_c = \frac{\sum_{m=1}^{M} s^m_{female,c}\bar{H}^m_{male}}{\sum_{m=1}^{M} s^m_{male,c}\bar{H}^m_{male}} - 1$. Like our potential wage indices in the main text, the only reason $I^{H,Major}_c$ only differs from 0 if men and women inhabit different majors. Likewise, $I^{H,Occ}_c$ is our potential hours index based on male annual hours worked in different occupations and is defined as $I^{H,Occ}_c = \frac{\sum_{o=1}^{O} s^m_{female,c}\bar{H}^o_{male}}{\sum_{o=1}^{O} s^m_{male,c}\bar{H}^o_{male}} - 1$.

As seen from Appendix Figure A8, women choose majors and occupations associated with lower potential annual hours worked. The major and occupation of women have converged to that of men over time in a way that implies women and men are choosing majors and occupations with more similar hours requirements. For the most recent cohorts, women are choosing both majors and occupations where potential annual hours worked are roughly 2 percent lower than men. Consistent with the literature, we find that college-educated women are choosing occupations with lower annual hours worked. We contribute to the hours literature by introducing the fact that college-educated women are choosing undergraduate majors associated with lower annual hours worked. We also show that the gender similarity of occupations and majors based on potential hours has been converging over time.

Appendix Figure A10 shows gender differences in the mapping of majors to occupations where we measure occupations in units of potential annual hours worked $\bar{H}^o_{male}$. Appendix Figure A10 is otherwise analogous to Figure 6 of the main text. To measure gender differences in occupation in hours units conditional on undergraduate major, we define $I^{H,Occ}_c|m$ that just recalculates $I^{H,Occ}_c$ (as defined above) restricting the sample to those individuals that chose major m. Consider individuals who choose to major in Engineering (Panel A, solid line). Women from the 1950 birth cohort who majored in Engineering subsequently work in occupations that had potential hours worked that were 2 percent lower than otherwise similar males. That gap disappeared for women who majored in Engineering after the 1975 birth cohort. For all majors, the gender gap in potential annual hours worked of occupation conditional on major has fallen over time. Women are now choosing occupations that are more similar in hours worked to men, conditional on occupation.

Appendix Figure A11 summarizes the mapping of majors to occupations where we measure occupations in potential hours space. This figure is otherwise analogous to Figure A9 in the main text. Women from the 1975 birth cohort are in occupations – conditional on major– that have annual hours worked that are three percent lower than comparable men. As a reminder, occupational potential wage differences, conditional on major, were about 9 percent for this cohort. Some of the reason that women may be choosing occupations with lower wages is that those occupations also have lower annual hours worked.

A5 A Regression Analysis of Gender Gaps in Employment

Our main analyses establish that (1) men and women sort differently into undergraduate major, (2) gendered sorting into college major has declined over time, and (3) conditional on major, women work in occupations with lower potential wages. Section examines the extent to which these patterns are associated with the gender wage gap among college graduates. In this section, we expand this discussion to explore effects of pre-market (major) and market specialization on gender gaps in *employment* among college graduates.

In Table A7, we report results from the following employment regressions:

$$Employed_i = \alpha + \beta Female_i + \delta_m Major_i + \Gamma X_i + \epsilon_i$$

where $Employed_i$ is a dummy variable equal to 1 if individual is employed and $Female_i$ is a dummy variable equal to 1 if the individual is female. In our sample from the 2014-2017 American Community Survey, college-educated women were 8.6 percentage points less likely to work than college-educated men conditional on demographics (Column 1). As seen in Column 2, controlling for major did not substantially alter the estimated gender gap in employment rates for women with a bachelor's degree.[22]

[22]This specification cannot control for occupation given that occupation is often not defined for those who

While controlling for undergraduate major reduces the estimated wage gap between college-educated men and women (as shown in Table 2), major is not important for understanding gender differences in employment rates for this group. Given the effect of major on the gender gap in wages, the extensive margin employment result is surprising. It points to the importance of potential effects of specialization on gender gaps in the intensive margin (hours worked) of employment.

A6 Wage Gap Decompositions

The bottom panel of Table 2 provides evidence of large convergence in the college gender wage gap across two 10-year birth cohorts: the 1958-1967 and 1978-1987 cohorts. In order to shed light on the power of our explanatory variables within cohort, we conduct a wage decomposition exercise. We report the formal results in Appendix Table A11 and discuss those results here.

As with the estimations in Table 2 and Table A10, the sample is restricted to include those with strong attachment to the labor market. We begin by estimating locally within birth cohort log wage equations for men only where race, state of residence, and marital status are categorical variables. As with all other specifications, the independent variable for $Major$ is the potential wage based on major, $\bar{Y}_i^m$, and the independent variable for *Occupation* is the potential wage based on occupation, $\bar{Y}_i^o$. Entries in the "Log Points" column are the within-cohort $male-female$ differences in the mean of the corresponding variable multiplied by the within-cohort *male* log wage coefficients of the corresponding variable. Entries in the "% Explained" column are the "Log Points" entries divided by the within-cohort *Total Raw Gap*.

In our model specification, occupational specialization plays the largest role in explaining the college gender wage gap. This is true for all 10-year birth cohorts. In the oldest birth cohort (1948-1957), occupation explains 43.9 percent of the gender wage gap. For the youngest birth cohort (1978-1987), the importance of occupation declines by 7 percentage points explaining 36.9 percent of the gender wage gap.

The results in Table 2 and Table A10 show that major and occupational sorting are *independently* related to the college gender wage gap. This finding is a contribution to the literature on the college gender wage gap and the role of pre-market specialization. In our decomposition exercise, we formally show that pre-labor market human capital specialization (major) has non-trivial importance in explaining the college gender wage gap. For the oldest birth cohort (1948-1957), major sorting explains 17.6 percent of the college gender wage gap. For the youngest birth cohort (1978-1987), major sorting explains 27.9 percent of the college gender wage gap. While much of the existing literature has focused on the role of human capital attainment with respect to the gender wage gap, our decomposition shows that human capital attainment *above and beyond a bachelor's degree* (such as a graduate degree) explains considerably less of the college gender wage gap than both pre-market and market human capital specialization.

---

are not working. Occupation is recorded for those who are not working only if they were employed at some point in the prior five years.

Finally, in thinking about the time series patterns, two findings are of particular interest. First, occupational specialization has become less important between the 1948-1957 and 1958-1967 birth cohorts and then mostly stabilized. For the 1948-1957 birth cohort, occupation explained 43.9 percent of the college gender wage gap. This fell to 38.0 percent for the 1958-1967 birth and was 37.5 percent and 36.9 percent for the 1968-1977 and 1978-1987 birth cohorts respectively. Second, college major has become increasingly important in explaining the gender wage gap for college graduates over time. It explained 10.3 percentage points *more* of the gap in the youngest (1978-1987) compared to the oldest (1948-1957) birth cohort.

A7 Robustness: Key Results

A7.1 Robustness Checks on Figures 2 and 4

In Figure 2 and Figure 4 of the main text, we restrict the sample on which our gender similarity indices are built to all individuals with reported majors (for $I_c^{DD,Major}$ and I_c^{Major}) or to all individuals with reported occupations (for $I_c^{DD,Occ}$ and I_c^{Occ}). Some individuals with reported majors are not working during the 2014-2017 period. Likewise, some individuals with reported occupations are not currently working (given the American Community Survey asks occupations for people who are currently not working but may have worked at some point in the prior five years). To see if including those who are currently not working bias our indices, we perform a robustness exercise by creating the respective indices restricted to a sample of individuals with strong attachment to the labor market as defined throughout our analysis (civilians who are not self-employed and report working for at least 30 hours a week for at least 27 weeks in the previous year).

The results of this exercise are shown in Appendix Figure A6. The results in Appendix Figure A6 are nearly identical to the results in Figure 2 and Figure 4 of the main text. This suggests that our results are insensitive to whether we include individuals with strong attachment to the labor market or all individuals when describing patterns of gender sorting in major (occupation) sorting.

Another potential issue with the results in Figure 2 and Figure 4 stems from the fact that the American Community Survey only asks undergraduate major in recent years (from 2009 to 2017). When we compare patterns for different birth cohorts, we risk confounding cohort and age effects. It is unlikely that this is problematic for our results about the convergence of undergraduate majors given that major is likely fixed over an individual's life cycle. Occupations are not fixed over the lifecycle, so this presents a potential problem with respect to how we have described occupational segregation by gender in Figure 2.

To address this and separate age and cohort effects on occupational segregation by gender, we use data from the 1980, 1990, and 2000 U.S. Censuses along with multiple waves of the American Community Survey to measure $I_c^{DD,Occ}$ for different birth cohorts at a constant age. The results are shown in Appendix Table A1. As with the results in the main text, birth cohort refers to 5-year birth cohorts centered around the birth year listed. Similarly, age refers to 5-year age ranges centered on the age listed. As seen in Appendix Table A1, age effects are not substantively biasing the main results shown in Figure 2 of the main text.

Within each age range, we see large convergence in the occupation similarity between men and women across birth cohorts.

A7.2 Robustness Checks on Table 2, Panel A

In Table A8, we report results from an alternate specification where we do not include demographic controls or time fixed effects. In Table A9, we report results from two alternate specifications where we aggregate majors and occupations to broader categories including including dummies for each broad major and occupation category. These exercises yield results that are very similar to those in Table 2.

Appendix Table A8 shows our key regression results without including our vector of demographic and time controls. Focusing on column 1 of the Table, the raw gender gap in wages among individuals without a bachelor's degree for our pooled sample was 26.8 log points. Including demographic controls as in column 1 of Table 2 of the main text, the gender gap only fell to 23.3 log points. The demographic controls only explain a small fraction of the gender wage gap among college graduates.

Appendix Table A9 shows the robustness results for the top panel of Table 2 of the main text to the alternate classification of majors and occupations. In our base specification in the main text, we used detailed occupation and major codes when defining the potential wage variables Y_i^m and Y_i^o. In the top panel of Appendix Table A9, we use the broad occupation and major codes to define Y_i^m and Y_i^o. In the bottom panel, we omit Y_i^m and Y_i^o altogether from the regression and instead include a vector of dummy variables for each broad major (occupation). The results of these alternate specifications are nearly identical to the results shown in Table 2 of the main text. This suggests that most of the variation in explaining gender wage gaps arises from differences across (as opposed to within) the broad major and occupation controls.

A7.3 Robustness Checks on Table 2, Panel B

The discussion in Section of our main regression results compares the gender gap in wages among college graduates from older and younger birth cohorts. Specifically, Panel B of Table 2 compares the 1958-1967 and the 1978-1987 birth cohorts.We show a reduction in both the raw gender wage gap and the gender wage gap controlling for major and occupation between older and younger generations of U.S. college graduates. We show that major remains mostly stable in terms of its explanatory power whereas the explanatory power of occupation declines across cohorts. In Appendix Table A10, we expand this cross-cohort analysis to include two additional 10-year birth cohorts: the 1948-1957 and the 1968-1977 birth cohorts.

Figure A1: List of Detailed and Broad Majors

Detailed Major	**Broad Major**
General Agriculture, Soil Science, Misc. Agriculture	Agriculture
Agriculture Production and Management	Agriculture
Animal Sciences	Agriculture
Food Science	Agriculture
Plant Science and Agronomy	Agriculture
Environmental Science	Environment and Natural Resources
Forestry	Environment and Natural Resources
Natural Resources Management	Environment and Natural Resources
Architecture	Architecture
Area, Ethnic, and Civilization Studies	Area, Ethnic, and Civilization Studies
Communications	Communications
Journalism	Communications
Mass Media	Communications
Advertising and Public Relations	Communications
Communication Technologies	Engineering
Computer and Information Systems	Computer and Information Systems
Computer Programming and Data Processing	Computer and Information Systems
Computer Science	Computer and Information Systems
Information Sciences	Computer and Information Systems
Computer Information Management and Security	Computer and Information Systems
Computer Networking and Telecommunications	Computer and Information Systems
Cosmetology Services and Culinary Arts	Cosmetology and Physical Fitness
General Education, School Counseling, Educational Administration and Supervision	Education Administration and Teaching
Elementary Education	Education Administration and Teaching
Mathematics Teacher Education	Education Administration and Teaching
Physical and Health Education Teaching	Education Administration and Teaching
Early Childhood Education	Education Administration and Teaching
Science and Computer Teacher Education	Education Administration and Teaching
Secondary Teacher Education	Education Administration and Teaching
Special Needs Education	Education Administration and Teaching
Social Science or History Teacher Education	Education Administration and Teaching
Teacher Education: Multiple Levels	Education Administration and Teaching
Language and Drama Education	Education Administration and Teaching
Art and Music Education	Education Administration and Teaching
Miscellaneous Education	Education Administration and Teaching

Figure A2: List of Detailed and Broad Majors (continued)

Detailed Major	**Broad Major**
Engineering: General, Military Technologies, Metallurgical, Biomedical, Geological and Geophysical, Mining and Mineral, Naval Architecture and Marine, Nuclear, Petroleum	Engineering
Aerospace Engineering	Engineering
Biological Engineering	Engineering
Chemical Engineering	Engineering
Civil and Architectural Engineering	Engineering
Computer Engineering	Engineering
Electrical Engineering, Electrical Engineering Technology, Electrical and Mechanic Repairs and Technologies	Engineering
Engineering Mechanics, Physics, and Science	Engineering
Environmental Engineering	Engineering
Industrial and Manufacturing Engineering, Precision Production and Industrial Arts	Engineering
Mechanical Engineering	Engineering
Miscellaneous Engineering	Engineering
Engineering Technologies	Engineering
Engineering and Industrial Management	Engineering
Industrial Production Technologies	Engineering
Mechanical Engineering Related Technologies	Engineering
Miscellaneous Engineering Technologies	Engineering
Linguistics, and Comparative Language and Literature	Linguistics and Foreign Languages
French, German, Latin and Other Common Foreign Languages	Linguistics and Foreign Languages
Other Foreign Languages	Linguistics and Foreign Languages
Family and Consumer Sciences	Family and Consumer Sciences
Pre-Law and Legal Studies, Court Reporting	Law
English Language and Literature	English and Literature
Composition and Speech	English and Literature
Liberal Arts	Liberal Arts and Humanities
Humanities	Liberal Arts and Humanities
Library Science	Education

Figure A3: List of Detailed and Broad Majors (continued)

Detailed Major	**Broad Major**
Biology, Misc. Biology, Pharmacology, Botany, Neuroscience, Genetics	Biology and Life Sciences
Biochemical Sciences	Biology and Life Sciences
Molecular Biology	Biology and Life Sciences
Ecology	Biology and Life Sciences
Microbiology	Biology and Life Sciences
Physiology	Biology and Life Sciences
Zoology	Biology and Life Sciences
Mathematics, Actuarial Science, Mathematics and Computer Science	Math and Statistics
Applied Mathematics	Math and Statistics
Statistics and Decision Science	Math and Statistics
Interdisciplinary,Multi-Disciplinary, Intercultural and International Studies	Multi-Disciplinary Studies (General)
Nutrition Sciences	Multi-Disciplinary Studies (General)
Physical Fitness, Parks, Recreation, and Leisure	Cosmetology and Physical Fitness
Philosophy and Religious Studies	Philosophy and Theology
Theology and Religious Vocations	Philosophy and Theology
Physical Sciences, Astronomy and Astrophysics, Geosciences, Nuclear, Industrial Radiology, and Biological Technologies	Physical Sciences
Atmospheric Sciences and Meteorology	Physical Sciences
Chemistry	Physical Sciences
Geology and Earth Science	Physical Sciences
Oceanography	Physical Sciences
Physics	Physical Sciences
Materials Science and Materials Engineering	Engineering
Multi-disciplinary or General Science	Physical Sciences
Psychology, Cognitive Science and Biopsychology, Social Psychology	Psychology
Educational Psychology	Psychology
Clinical Psychology	Psychology
Counseling Psychology	Psychology
Industrial and Organizational Psychology	Psychology
Miscellaneous Psychology	Psychology

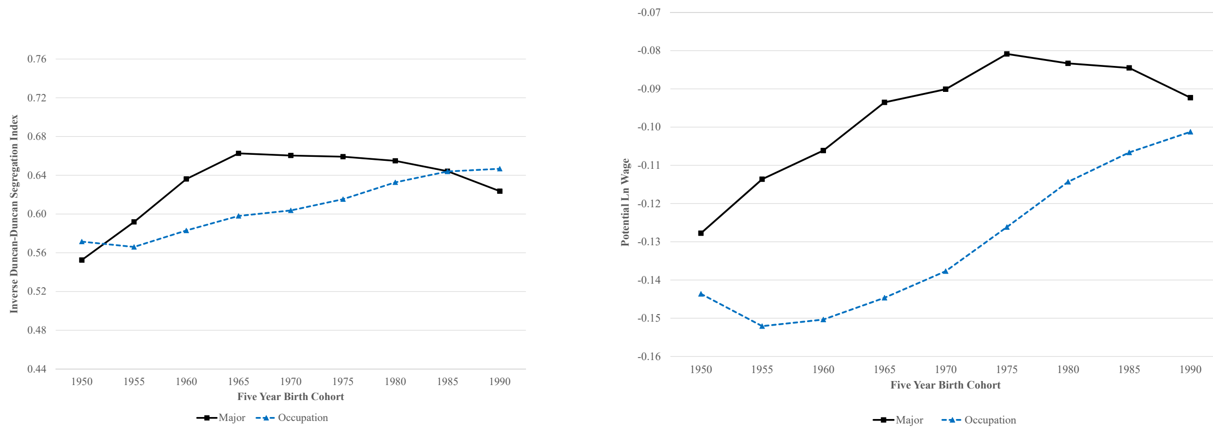
Figure A4: List of Detailed and Broad Majors (continued)

Detailed Major	Broad Major
Criminal Justice and Fire Protection	Criminal Justice and Fire Protection
Public Administration	Public Affairs, Policy, and Social Work
Public Policy	Public Affairs, Policy, and Social Work
Human Services and Community Organization	Public Affairs, Policy, and Social Work
Social Work	Public Affairs, Policy, and Social Work
General Social Sciences	Social Sciences
Economics, Agricultural Economics, Business Economics	Social Sciences
Anthropology and Archeology	Social Sciences
Criminology	Social Sciences
Geography	Social Sciences
International Relations	Social Sciences
Political Science and Government	Social Sciences
Sociology	Social Sciences
Miscellaneous Social Sciences	Social Sciences
Construction Services	Construction Services
Transportation Sciences and Technologies	Construction Services
Fine Arts, Commercial Art and Graphic Design, Film, Video and Photographic Arts, Studio Arts, Miscellaneous Fine Arts	Fine Arts
Drama and Theater Arts, Music, Visual and Performing Arts	Fine Arts
Art History and Criticism	Fine Arts
General Medical and Health Services	Nursing, Medical and Health Sciences
Communication Disorders Sciences and Services	Nursing, Medical and Health Sciences
Health and Medical Administrative Services	Nursing, Medical and Health Sciences
Medical Assisting Services	Nursing, Medical and Health Sciences
Medical Technologies Technicians	Nursing, Medical and Health Sciences
Health and Medical Preparatory Programs	Nursing, Medical and Health Sciences
Nursing	Nursing, Medical and Health Sciences
Pharmacy, Pharmaceutical Sciences, and Administration	Nursing, Medical and Health Sciences
Treatment Therapy Professions	Nursing, Medical and Health Sciences
Community and Public Health	Nursing, Medical and Health Sciences
Miscellaneous Health Medical Professions	Nursing, Medical and Health Sciences

Figure A5: List of Detailed and Broad Majors (continued)

Detailed Major	**Broad Major**
General Business	Business
Accounting	Business
Business Management and Administration	Business
Operations, Logistics and E-Commerce	Business
Marketing and Marketing Research	Business
Finance	Business
Human Resources and Personnel Management	Business
International Business	Business
Hospitality Management	Business
Management Information Systems and Statistics	Business
Miscellaneous Business and Medical Administration	Business
History	History
United States History	History

Figure A6: Gender Similarity in Major and Occupational Sorting by Cohort, Strongly Attached Sample

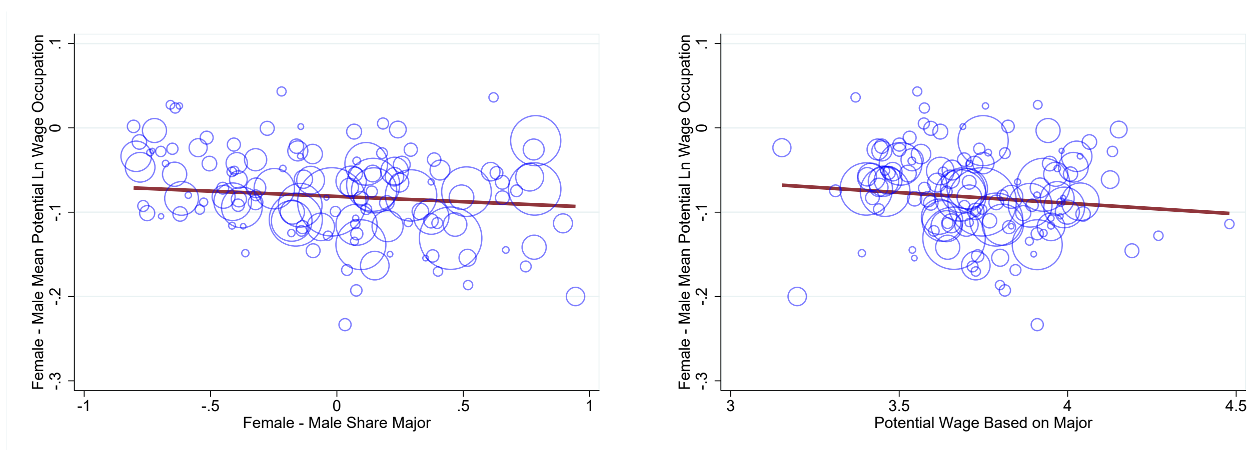


Panel A: Segregation Index Index

Panel B: Potential Wage Index

Notes: Figure plots the inverse segregation index (left panel) and potential wage index (right panel) for different cohorts conditioning on strong attachment to the labor market. The solid line in each panel show the indices for major. The dashed line in each panel show the indices for occupation. Data from the 2014-2017 ACS and are restricted to those with at least a bachelor's degree. See text for additional details.

Figure A7: Cross Major Variation in Within-Major Gender Differences in Potential Wage by Occupation, 1968-1977 Birth Cohort

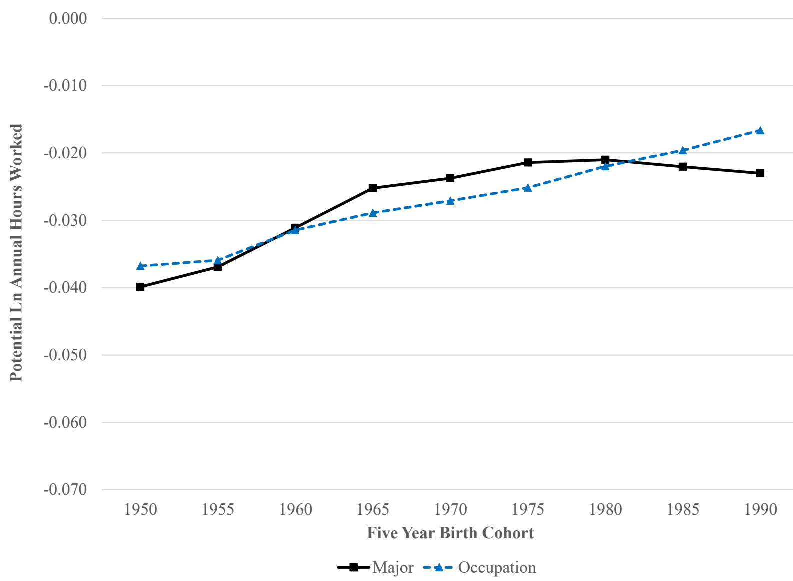


Panel A: Gender Composition of Major

Panel B: Potential Income of Major

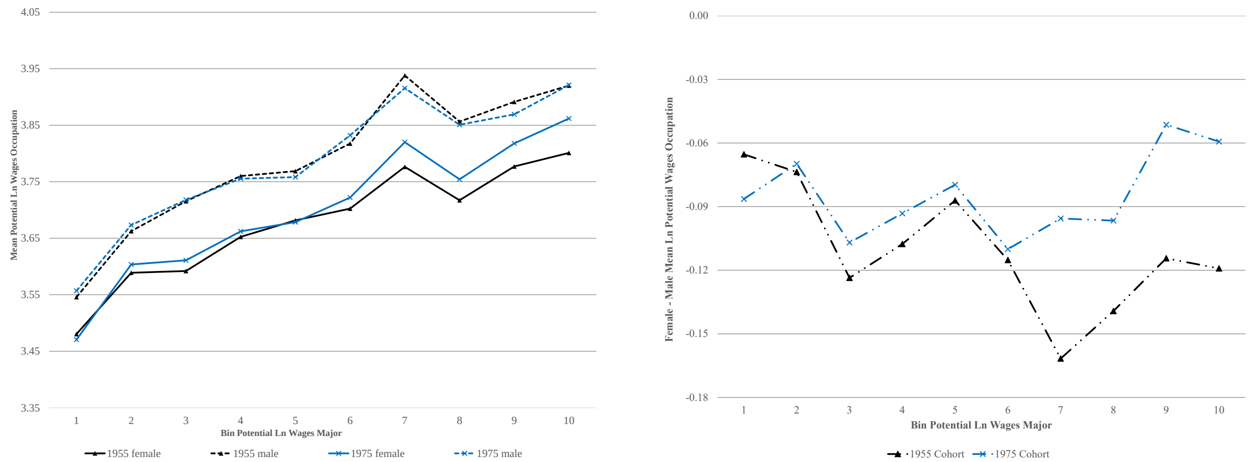
Notes: These figures show cross-major variation in $I_c^{Occ|m}$ as a function of how female-dominated is the major (panel A) and average major potential income (panel B). See text for additional details. Each observation in both panels is a detailed major. Data shown only for the 1968-1977 birth cohort. Both panels include a fitted regression line. The slopes of the regression lines are -0.013 (standard error = 0.009) and -0.025 (standard error = 0.017), respectively.

Figure A8: Potential Hours Worked Index in Major and Occupation by Cohort



Notes: Figure plots the potential hours worked indices for major and occupation, across different cohorts of US college graduates. The solid line shows the index for major ($I_c^{H,Major}$). The dashed line shows the index for occupation ($I_c^{H,Occ}$). Data from the 2014-2017 ACS and are restricted to those with at least a bachelor's degree.

Figure A9: Mapping of Potential Wage by Major to Potential Wage by Occupation, by Gender and Cohort

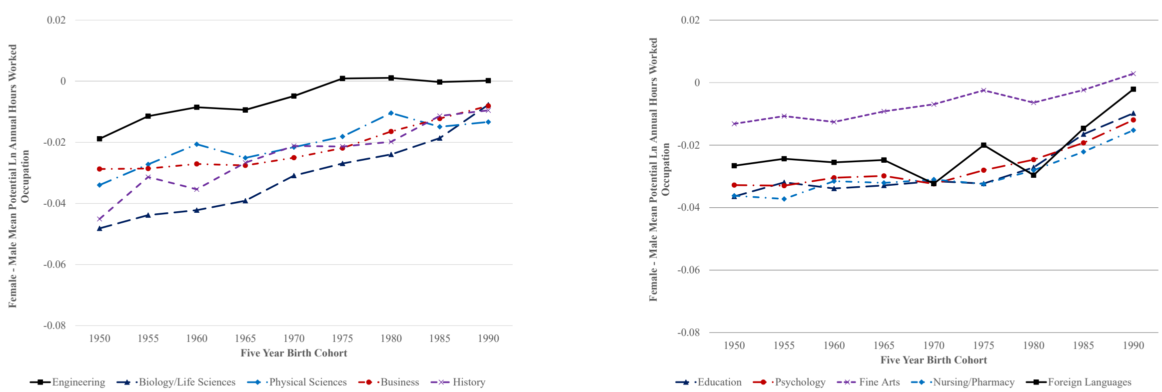


Panel A: Levels
Selected Cohorts

Panel B: Differences
Selected Cohorts

Notes: These figures show the mapping between major and occupation. On the x-axes, we have binned majors based on $\bar{Y}^{m}_{male}$, the log wage deciles of native, white men age 43 to 57 in major m. On the y-axis in Panel A, we report $I_c^{P,O|d,g}$, the mean log potential occupational wages within these deciles described separately by gender and cohort. In Panel B, the y-axis reports female - male differences in $I_c^{P,O|d,g}$ for two of the cohorts.

Figure A10: Within-Major Gender Differences in Potential Hours by Occupation, by Gender and Cohort

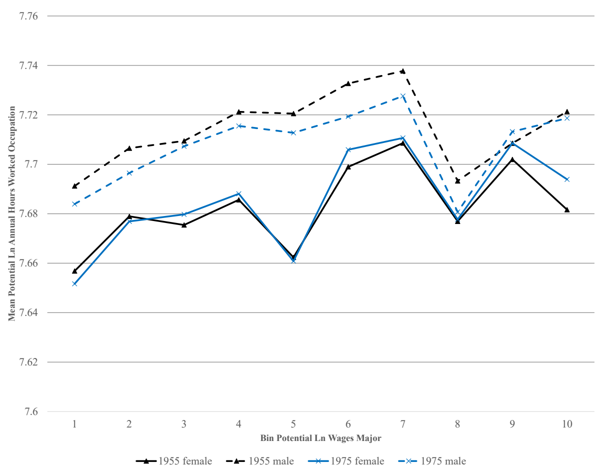


Panel A: Male-Dominated
Majors

Panel B: Female-Dominated
Majors

Notes: These figures show the trends in $I_c^{H,Occ|m}$ conditional on having graduated with major m. Panel A are male-dominated majors. Panel B are female-dominated majors. As with the left panel of Figure **??**, potential wage in an occupation, $\bar{H}^{o}_{male}$, is computed using only annual hours worked of native white males 43-57 who are working full time in the 2014-2017 ACS.

Figure A11: Mapping of Potential Wages by Major to Potential Hours by Occupation, by Gender and Cohort



Panel A: Levels

Panel B: Differences

Notes: These figures show the mapping between major and occupation. On the x-axes, we have binned majors based on $\bar{Y}^{m}_{male}$, the log wage deciles of native, white men age 43 to 57. On the y-axis in Panel A, we report $I_c^{H,Occ|d,m}$, the mean log potential occupational hours worked within these deciles described separately by gender and cohort. In Panel B, the y-axis reports female - male differences in $I_c^{H,Occ|d,m}$ for two of the cohorts.

Table A1: Robustness of Trends in Inverse Duncan-Duncan Index for Gender Occupational Similarity, Controlling for Age Effects

Cohort	30	35	40	45	50	55
1925						0.386
1930					0.393	
1935				0.402		0.451
1940			0.435		0.485	
1945		0.464		0.510		0.511
1950	0.501		0.519		0.519	
1955		0.541		0.527		0.544
1960	0.610		0.572		0.566	0.571
1965		0.605		0.579	0.587	
1970	0.620		0.599	0.592		
1975		0.613	0.600			
1980	0.622	0.612				
1985	0.627					

Note: This table computes the inverse Duncan-Duncan index for gender similarity in occupational sorting ($I_c^{DD,Occ}$) for different birth cohorts and age ranges. See main text for construction of the index. Increasing values reflect a movement toward gender parity in sorting. Cohorts are five year birth cohorts centered around the birth cohort listed. Age are five year age ranges centered around the age listed. Data come from the 1980, 1990, and 2000 U.S. Censuses as well as various years of the American Community Survey.

Table A2: Occupational Concentration Conditional on Major, 1968-77 Birth Cohort

	Herfindahl-Herschman Index $HHI_{g,c}^{Major}$	
Broad Major	Men	Women
Agriculture	0.10	0.08
Environment and Natural Resources	0.10	0.09
Architecture	0.26	0.21
Area, Ethnic, and Civilization Studies	0.09	0.10
Communications	0.12	0.12
Computer and Information Sciences	0.18	0.13
Cosmetology Services and Physical Fitness	0.10	0.10
Education Administration and Teaching	0.29	0.48
Engineering	0.16	0.13
Linguistics and Foreign Languages	0.09	0.11
Family and Consumer Sciences	0.11	0.15
Law	0.13	0.14
English and Literature	0.09	0.11
Liberal Arts and Humanities	0.09	0.14
Biology and Life Sciences	0.12	0.10
Math and Statistics	0.11	0.13
Multi-Disciplinary Studies (General)	0.09	0.11
Philosophy and Theology	0.10	0.09
Physical Sciences	0.09	0.08
Psychology	0.09	0.11
Criminal Justice and Fire Protection	0.19	0.10
Public Affairs, Policy, and Social Work	0.12	0.18
Social Sciences	0.11	0.10
Construction Services	0.29	0.25
Fine Arts	0.08	0.09
Nursing, Medical and Health Sciences	0.25	0.41
Business	0.16	0.14
History	0.10	0.11

Note: Table shows occupational concentration within major category for men and women born between 1968 and 1977 for different majors. Specifically, this table reports $HHI_{g,c}^{Major}$ from the 2014-2017 ACS. We use broad major and broad occupation categories. Values closer to 0 reflect more dispersion.

Table A3: Major to Occupation Mapping Measure, 1968-1977 Birth Cohort

Detailed Major	**Female-Male Mean Potential Ln Wage Occupation**
Zoology	-0.233
Early Childhood Education	-0.200
Microbiology	-0.193
Miscellaneous Psychology	-0.186
Linguistics, and Comparative Language and Literature	-0.170
International Business	-0.169
Nutrition Sciences	-0.164
Interdisciplinary,Multi-Disciplinary Studies	-0.163
Clinical Psychology	-0.154
Health and Medical Administrative Services	-0.154
Pre-Law and Legal Studies, Court Reporting	-0.152
Miscellaneous Social Sciences	-0.150
Cosmetology Services and Culinary Arts	-0.149
Biochemical Sciences	-0.146
Educational Psychology	-0.145
Family and Consumer Sciences	-0.142
Biology, Misc. Biology, Pharmacology, Botany, Neuroscience, Genetics	-0.139
Public Policy	-0.134
Psychology, Cognitive Science and Biopsychology, Social Psychology	-0.131
Molecular Biology	-0.128
Physiology	-0.126
Physical Sciences, Astronomy and Astrophysics, Geosciences, Nuclear, Industrial Radiology, and Biological Technologies	-0.125
Criminology	-0.122
Miscellaneous Business and Medical Administration	-0.118
Mathematics, Actuarial Science, Mathematics and Computer Science	-0.117
Computer Programming and Data Processing	-0.117
Liberal Arts	-0.117
Environmental Engineering	-0.116
Marketing and Marketing Research	-0.115
French, German, Latin and Other Common Foreign Languages	-0.115
Health and Medical Preparatory Programs	-0.114
Communication Disorders Sciences and Services	-0.113
Community and Public Health	-0.113
Humanities	-0.112
Criminal Justice and Fire Protection	-0.110
General Medical and Health Services	-0.110
General Business	-0.109

Table A4: Major to Occupation Mapping Measure, 1968-1977 Birth Cohort (continued)

Detailed Major	Female-Male Mean Potential Ln Wage Occupation
Food Science	-0.107
Sociology	-0.105
Engineering Mechanics, Physics, and Science	-0.105
Physics	-0.102
Transportation Sciences and Technologies	-0.101
Chemistry	-0.100
Public Administration	-0.099
Area, Ethnic, and Civilization Studies	-0.099
Computer Information Management and Security	-0.097
Science and Computer Teacher Education	-0.096
Finance	-0.094
Industrial Production Technologies	-0.093
Political Science and Government	-0.092
Information Sciences	-0.092
General Social Sciences	-0.089
Geology and Earth Science	-0.088
Materials Science and Materials Engineering	-0.088
Business Management and Administration	-0.088
Economics, Agricultural Economics, Business Economics	-0.088
Geography	-0.085
Miscellaneous Education	-0.084
Computer Science	-0.084
Teacher Education: Multiple Levels	-0.083
Oceanography	-0.083
Treatment Therapy Professions	-0.082
Computer and Information Systems	-0.082
English Language and Literature	-0.080
Operations, Logistics and E-Commerce	-0.080
Biological Engineering	-0.080
General Education, School Counseling, Educational Administration and Supervision	-0.076
Ecology	-0.076
Miscellaneous Health Medical Professions	-0.075
Communications	-0.074
Elementary Education	-0.072
History	-0.072
Plant Science and Agronomy	-0.072
Management Information Systems and Statistics	-0.071

Table A5: Major to Occupation Mapping Measure, 1968-1977 Birth Cohort (continued)

Detailed Major	**Female-Male Mean Potential Ln Wage Occupation**
Secondary Teacher Education	-0.071
Accounting	-0.067
Anthropology and Archeology	-0.065
Art History and Criticism	-0.064
Industrial and Organizational Psychology	-0.064
Drama and Theater Arts, Music, Visual and Performing Arts	-0.063
Physical Fitness, Parks, Recreation, and Leisure	-0.062
Chemical Engineering	-0.061
Environmental Science	-0.061
Social Work	-0.058
Art and Music Education	-0.058
Civil and Architectural Engineering	-0.055
International Relations	-0.055
Hospitality Management	-0.054
Human Services and Community Organization	-0.053
Computer Networking and Telecommunications	-0.052
Language and Drama Education	-0.052
Journalism	-0.051
Communication Technologies	-0.051
Human Resources and Personnel Management	-0.050
Statistics and Decision Science	-0.048
Mechanical Engineering	-0.047
Advertising and Public Relations	-0.044
Fine Arts, Commercial Art and Graphic Design, Film, Video and Photographic Arts, Studio Arts, Miscellaneous Fine Arts	-0.043
Industrial and Manufacturing Engineering, Precision Production and Industrial Arts	-0.042
Engineering Technologies	-0.042
Architecture	-0.042
Other Foreign Languages	-0.039
Philosophy and Religious Studies	-0.038
Medical Technologies Technicians	-0.038
Electrical Engineering, Electrical Engineering Technology, Electrical and Mechanic Repairs and Technologies	-0.034
Applied Mathematics	-0.034
Mass Media	-0.031
Intercultural and International Studies	-0.030
Mechanical Engineering Related Technologies	-0.029
Aerospace Engineering	-0.028
Physical and Health Education Teaching	-0.027

Table A6: Major to Occupation Mapping Measure, 1968-1977 Birth Cohort (continued)

Detailed Major	Female-Male Mean Potential Ln Wage Occupation
Atmospheric Sciences and Meteorology	-0.027
Mathematics Teacher Education	-0.026
Special Needs Education	-0.026
Miscellaneous Engineering Technologies	-0.025
Theology and Religious Vocations	-0.023
Social Science or History Teacher Education	-0.022
General Agriculture, Soil Science, Misc. Agriculture	-0.020
Computer Engineering	-0.017
Nursing	-0.015
Agriculture Production and Management	-0.012
Animal Sciences	-0.004
Engineering: General, Military Technologies, Metallurgical, Biomedical, Geological and Geophysical, Mining and Mineral, Naval Architecture and Marine, Nuclear, Petroleum	-0.003
Pharmacy, Pharmaceutical Sciences, and Administration	-0.002
Natural Resources Management	-0.001
United States History	0.002
Construction Services	0.002
Composition and Speech	0.005
Forestry	0.024
Engineering and Industrial Management	0.026
Miscellaneous Engineering	0.027
Counseling Psychology	0.036
Misc. Biology	0.043

Table A7: Major Sorting and Gender Gaps in Employment

	Employment Rate	
Variable	(1)	(2)
$Female_i$	-0.088	-0.083
	(0.003)	(0.003)
$\bar{Y}_i^m$		0.045
		(0.003)
Controls	Yes	Yes
R^2	0.13	0.13

Note: Table shows estimates from regression $Employed_i = \alpha + \beta Female_i + \delta_m Major_i + \Gamma X_i + \epsilon_i$ where $Employed_i$ is a dummy variable equal to 1 if individual is employed and $Female_i$ is a dummy variable equal to 1 if the individual is female. Sample size is 3,428,990.

Table A8: Major, Occupation and Gender Gaps in Wages and Employment, No Controls

	Log Wages				Employment Rate	
Variable	(1)	(2)	(3)	(4)	(5)	(6)
$Female_i$	-0.268	-0.189	-0.160	-0.135	-0.075	-0.066
	(0.007)	(0.006)	(0.005)	(0.004)	(0.003)	(0.003)
$\bar{Y}_i^m$		0.827		0.355		0.091
		(0.017)		(0.014)		(0.005)
$\bar{Y}_i^o$			0.862	0.793		
			(0.011)	(0.009)		
Controls	No	No	No	No	No	No
R^2	0.04	0.10	0.23	0.23	0.01	0.01

Note: This table is a robustness check on panel (a) of Table 2 with no demographic or time controls. Sample size for columns 1-4 is 2,270,392. Sample size for columns 5-6 is 3,428,990.

Table A9: Major, Occupation and Gender Gaps in Wages and Employment, Alternative Specifications Using Broad Major and Occupations

(a) Log Wage and Employment Rate Regressions with Broad Major and Occupation Potential Wage Indices, Pooled Cohorts

	Log Wages				Employment Rate	
Variable	(1)	(2)	(3)	(4)	(5)	(6)
$Female_i$	-0.232	-0.172	-0.167	-0.141	-0.088	-0.083
	(0.006)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)
$\bar{Y}_i^m$		0.832		0.461		0.061
		(0.022)		(0.015)		(0.004)
$\bar{Y}_i^o$			0.750	0.668		
			(0.013)	(0.010)		
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.22	0.26	0.33	0.34	0.13	0.13

(b) Log Wage and Employment Rate Regressions with Flexible, Broad Major and Occupation Dummies, Pooled Cohorts

	Log Wages				Employment Rate	
Variable	(1)	(2)	(3)	(4)	(5)	(6)
$Female_i$	-0.232	-0.169	-0.168	-0.143	-0.088	-0.083
	(0.006)	(0.005)	(0.004)	(0.004)	(0.003)	(0.003)
Major dummies	No	Yes	No	Yes	No	Yes
Occupation dummies	No	No	Yes	Yes	No	No
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.22	0.27	0.34	0.35	0.13	0.13

Note: This table is a robustness check on the main results in Panel (a) of Table 2 using two alternate ways to control for occupation and major sorting. In Panel (a) of this table, we include as independent variables measures of potential wages determined by the broad majors and occupations instead of detailed majors and occupations. In panel (b), we include as independent variables vectors of broad major dummies and occupation dummies instead of our potential wage controls. Sample size for panel A columns 1-4 is 2,256,630. Sample size for panel A columns 5-6 is 3,428,990. Sample size for panel B columns 1-4 is 2,256,630. Sample size for panel B columns 5-6 is 3,428,990.

Table A10: Major, Occupation and Gender Gaps in Wages and Employment

(a) Log Wage Regressions, Older Cohorts

	1948-1957 Birth Cohorts			1958-1967 Birth Cohorts		
Variable	(1)	(2)	(3)	(4)	(5)	(6)
$Female_i$	-0.291	-0.163	-0.130	-0.322	-0.198	-0.168
	(0.009)	(0.005)	(0.006)	(0.008)	(0.005)	(0.004)
$\bar{Y}_i^m$			0.366			0.410
			(0.018)			(0.016)
$\bar{Y}_i^o$		0.886	0.819		0.909	0.823
		(0.016)	(0.013)		(0.015)	(0.012)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.12	0.30	0.31	0.13	0.32	0.33

(b) Log Wage Regressions, Younger Cohorts

	1968-1977 Birth Cohorts			1978-1987 Birth Cohorts		
Variable	(1)	(2)	(3)	(4)	(5)	(6)
$Female_i$	-0.271	-0.169	-0.144	-0.155	-0.093	-0.065
	(0.008)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)
$\bar{Y}_i^m$			0.410			0.443
			(0.015)			(0.010)
$\bar{Y}_i^o$		0.850	0.766		0.599	0.513
		(0.014)	(0.011)		(0.008)	(0.007)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.14	0.31	0.33	0.13	0.25	0.27

Note: The specifications in this table are the same as the specifications shown in Panel (b) of Table 2. Columns 4-6 from this table are exactly the same as the results in Panel (b) of Table 2. The new results in this table are in columns 1-3 of both panels that show the results for alternate birth cohorts. Sample size for panel (a) columns 1-3 is 331,678. Sample size for panel (a) columns 4-6 is 533,348. Sample size for panel (b) columns 1-3 is 543,452. Sample size for panel (b) columns 4-6 is 614,106.

Table A11: Wage Decompositions: Explanatory Variables

(a) Older Cohorts

	1948-1957 Birth Cohort		1958-1967 Birth Cohort	
Variable	(Log Points)	(% Explained)	(Log Points)	(% Explained)
Race	0.0008	0.25%	0.0011	0.32%
State	0.0004	0.14%	0.0002	0.06%
Marital Status	0.0287	9.19%	0.0164	4.74%
Masters	-0.0048	-1.55%	-0.0034	-0.99%
Doctorate	0.0056	1.80%	0.0022	0.63%
Major	0.0549	17.57%	0.0547	15.81%
Occupation	0.1371	43.86%	0.1314	37.97%
Year	-0.0006	-0.19%	-0.0001	-0.04%
Explained	0.2221	71.07%	0.2025	58.51%
Unexplained	0.0904	28.93%	0.1436	41.49%
Total Raw Gap	0.31		0.35	

(b) Younger Cohorts

	1968-1977 Birth Cohort		1978-1987 Birth Cohort	
Variable	(Log Points)	(% Explained)	(Log Points)	(% Explained)
Race	0.0004	0.13%	0.0001	0.04%
State	0.0001	0.03%	0.0001	0.05%
Marital Status	0.0146	5.03%	0.0002	0.11%
Masters	-0.0080	-2.76%	-0.0064	-4.09%
Doctorate	0.0007	0.25%	0.0000	0.03%
Major	0.0444	15.27%	0.0438	27.85%
Occupation	0.1090	37.53%	0.0579	36.86%
Year	-0.0003	-0.09%	0.0001	0.03%
Explained	0.1609	55.39%	0.0956	60.87%
Unexplained	0.1296	44.61%	-0.0615	39.13%
Total Gap	0.29		0.16	

Note: Sample restrictions and cohorts consistent with Table A10. In these estimations, race, state of residence, and marital status are categorical variables instead of flexible dummies. This does not affect our main results and is only for ease in decomposition and display. As with all other specifications, the independent variable for $Major$ is $\bar{Y}_i^m$, and the independent variable for *Occupation* is $\bar{Y}_i^o$. Entries in the "Log Points" column are the within-cohort $male - female$ differences in the mean of the corresponding variable multiplied by the within-cohort *male* log wage coefficients of the corresponding variable. Entries in the "% Explained" column are the "Log Points" entries divided by the within-cohort Total Raw Gap. The Total Raw Gap differs from the $Female_i$ in Column (1) of Table A10 in that it is the raw gender wage gap with no controls and the gender wage gap displayed as the coefficient for $Female_i$ in Column (1) of Table A10 includes demographic controls.