Occupational Segregation by Gender of Recent College Graduates

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Abstract

Using the American Community Survey (ACS) and the Occupational Information Network (O*NET), this paper analyses whether men and women with the same college major segregate into different occupations associated with gendered occupational traits at the beginning of their careers before they have children. This paper finds that there are significant gender differences in occupational traits within most college majors with male graduates being in more competitive and inflexible occupations while female graduates are in occupations with higher levels of social contribution. If women have the same average occupational traits as men within major, the gender wage gap of recent, young college graduates decreases by 16.68%. In addition, if men and women are equally represented in each college major and have the same average occupational traits within major, the gender wage gap of young graduates is nearly eradicated. If this occupational segregation is due to gender differences in occupational preferences, then policies to decrease the gender wage gap of college graduates may need to require companies to have more flexible work arrangements and compensate occupations which contribute to society more.

Keywords: Occupational Segregation, College Major, Gender Wage Gap, Simulation

1 Introduction

Gender differences in college major have been shown in previous research to significantly contribute to the gender wage gap of college educated men and women (Black et al., 2008; Machin and Puhani, 2003; Weinberger, 1999, 1998; Brown and Corcoran, 1997; Gerhart, 1990; Daymont and Andrisani, 1984). These papers show that men (women) choose college majors which are associated with higher (lower) wages. These findings indicate that to decrease the gender wage gap of college graduates, society should encourage women to choose majors which lead to more lucrative occupations. Currently, there is a large push in the United States to encourage women to choose STEM majors (science, technology, engineering and mathematics) with the hopes of decreasing the gender wage gap. However, college majors and occupational decisions are not perfectly correlated. Altonji et al. (2016a) states when an individual chooses their occupation following college that the utility maximizing choice of occupation will depend on an individuals preferences for non-pecuniary characteristics of an occupation. Therefore, encouraging women into majors associated with higher wages may not lead to as large of a decrease in the gender wage gap one may expect if female graduates sort into occupations associated with lower wages within major.

This paper fills a gap in the literature by analysing whether there is occupational segregation by gender within college major for recent college graduates before they have children. By using the American Community Survey (2012-2017) and the Occupational Information Network (O*NET) database, I am able to observe whether men and women with the same college major sort into different occupations associated with gendered occupational traits such as: competitiveness, social contribution (how much the job contributes to society) and inflexibility. Using simulation techniques, this paper finds that if female graduates attain occupations with the same average levels of competitiveness, social contribution and inflexibility as male graduates with the same major, this results in a reduction of the gender wage gap of recent college graduates by 16.68%. This reduction is due to male graduates

attaining more competitive and inflexible occupations which are positively compensated in the labour market and women attaining occupations with higher levels of social contribution which are negatively compensated. In addition, if female graduates attain occupations with the same average occupational traits as male graduates while men and women are equally represented in each college major, this reduces the gender wage gap by 87.55%. These findings suggest that occupational segregation by gender exists within detailed college major even when the sample is restricted to comparable men and women as they do not have children and are at the beginning stages of their careers.

Recent research by economists has expanded our knowledge of occupational segregation by analysing if men and women prefer and/or attain occupations associated with gendered occupational traits.[1] This paper focuses on three occupational traits where occupational segregation by gender has been found not only in the working-age population but also in the context of highly educated men and women. First, there is a plethora of experimental research about gender differences in preferences for competition.[2] This research finds, on average, that men prefer competitive environments more than women. Additional papers have found that men are more likely to apply for jobs which have more competitive pay schemes than women which usually results in higher wages for men (Flory et al., 2014; Manning and Saidi, 2010; McGee et al., 2015; Kleinjans, 2009; Niederle and Vesterlund, 2007). Goldin (2014) states that competition may affect wages the most in the context of high skilled jobs which typically require a college education. Focusing on a sample of undergraduate and MBA students, Reuben et al. (2017) and Reuben et al. (2015) found that gender differences in competitiveness significantly contributed to the gender gap in expected and actual earnings and this difference in wages could be attributed to men and women wanting and attaining different occupations.

Second, there is a set of literature about women preferring and attaining occupa-

[1]See Cortes and Pan (2018) for a literature review.
[2]See Gneezy et al. (2003) and Azmat and Petrongolo (2014) for literature reviews.

tions associated with contributing to society (Kerr, 2019; Baker and Cornelson, 2018; Cortes and Pan, 2018; Fortin, 2008; England et al., 2002). Fortin (2008) found that gender differences in preferences for occupations which contributed to society measured before entry into the labour market, contributed as much to the gender wage gap as gender differences in labor market experience. Grove et al. (2011) found in a sample of MBA students that the gender wage gap could be partially explained by female graduates attaining occupations associated with higher levels of contribution to society. There is also a literature about how occupations associated with caring for individuals are predominately filled by women and that these occupations are paid significantly less than other occupations which require the same level of education and work experience (Folbre, 2017; England et al., 2002).

Third, there is substantial literature about gender differences in preferences for workplace flexibility. Previous papers have found that women prefer to have the option to work part-time and are willing to take a job with lower pay to accommodate this preference (Cortes and Pan, 2018, 2016; Wiswall and Zafar, 2016; Flabbi and Moro, 2012; Goldin and Katz, 2011). Goldin (2014) and Gicheva (2013) found non-linear increasing returns to long work weeks significantly contributes to the gender wage gap and that this is predominately found in occupations which require highly educated workers. In addition, using an exogenous shock to restriction of weekly hours of medical residents in the US, Wasserman (2015) found that a reduction in the weekly hours for medical specialities with longest work weeks (ie Surgery) caused more women to enter that specialty.

There are two main contributions of this research. The first contribution shows that there is occupational segregation of occupational traits by gender within college major. A few papers have discussed occupational segregation within major; however, none of these papers focused on the traits of the occupations. Joy (2006, 2000) found occupational segregation by gender of college graduates when using eight broad occupational categories and six broad field of study categories. Joy (2006, 2000) found when controlling for college major that

women (men) were more likely to end up in clerical (managerial) occupations. I contribute to these papers by using detailed college majors and information on the traits of more than 400 occupations. Having detailed college majors and occupational codes is important as analysing broader categories may hide which specific majors have large occupational differences by gender. In addition, to further our understanding of why graduates do not choose the same occupations, it is important to understand the traits of the occupations that they attain. I also contribute to these papers as I use a recent data set (2012-2017) which puts the analysis in the context of today while Joy (2006, 2000) used data from the early 1990s.

The second contribution of this research shows using simulation techniques similar to Thornton and McDonald (2015); McDonald and Thornton (2007); Eide (1994) that eliminating gender differences in occupational traits within college major decreases the gender wage gap of young college graduates. These previous papers did not attempt to reduce occupational segregation within college major in their simulations as they focused on simulating gender wage gaps if women had the same college majors as men. In addition, in their simulations, the total number of graduates of a specific major would change as they would be adding or subtracting women to each major to match the number of men. This assumes that wages in the labour market would remain the same even though the number of graduates with specific degrees may in fact double (e.g. Computer Science or Engineering degrees). By restricting the total number of graduates for each major to remain the same in my simulations (by only changing the gender proportions within major), I do not have to make this strong assumption.

This paper provides evidence that occupational segregation by gender occurs within college major. As these gender differences in occupational traits may be a result of gender differences in occupational preferences, this makes an interesting policy discussion as it may not be efficient to encourage men and women to take occupations that they do not prefer.

Rather, in order to decrease the gender wage gap for college graduates, it may be necessary to compensate jobs differently (or structure jobs differently) so occupational segregation based on these traits does not have such a large association with the gender wage gap.

2 Data

2.1 American Community Survey

The first dataset used in this paper is the American Community Survey (ACS) 2012-2017. There are a few reasons why I use this dataset for my analysis. First, this is a nationally representative dataset which surveys at least two million individuals each year which enables a very large sample size. Second, as this is a recent dataset, it can be analysed in the context of the current labour market. Third, the ACS has collected information on peoples college major from 2009 onwards. If a respondent stated that they have obtained at least a bachelors degree, they are asked to state their bachelors degree major. These responses are coded in both general codes (39 categories) and detailed codes (171 categories).

In addition to having information about individuals college majors, the ACS also collects detailed information on an individuals occupation using 4-digit occupational codes. These codes offer information on more than 400 detailed occupations of respondents. This enables analysis of gender differences in occupations for individuals who have the same college major. Furthermore, the ACS collects information about the weeks and hours worked for the previous year. I then calculate the hourly wage of an individual by their annual earnings divided by the product of the number of weeks they worked and their usual hours they worked per week. Furthermore, I calculate the average hours worked in a given occupation of full-year employed individuals to be used as a proxy for flexibility of an occupation as occupations with lower average weekly hours are likely to enable part-time work than occupations with

long weekly hours. In a recent working paper, Denning et al. (2019) use this measure to indicate one's expectation of the hours worked in an occupation. They found that women sorting into these occupations contributes to the gender wage gap.

2.2 O*NET Database

The second dataset used is the O*NET (Occupational Information Network) database constructed by the U.S. Department of Labor, which has replaced the Dictionary of Occupational Titles (DOT) database (Council et al., 2010). The O*NET database is updated annually and is freely available online. This database contains hundreds of descriptors for over 1,000 occupations in the United States that detail the skills and characteristics of occupations. Data on individual occupations is collected by first randomly sampling businesses which have been identified as likely to hold the occupation in question and then randomly sampling individuals within those businesses who are employed in that occupation. On average, each occupation has a sample of approximately 33 individuals who are employed in the occupation or occupational experts that have recently worked in the occupation for occupations which are scarce. Therefore, the O*NET measures are not from a single respondent but the average response from a sample of respondents (Council et al., 2010).

The main categories that the O*NET database collects information on individual occupations are: abilities, background, education and training, work activities, knowledge, skills, work context and work styles. The variables I am interested in researching are: competitiveness and social contribution of a given occupation which were both used in Cortes and Pan (2018) and Baker and Cornelson (2018). Each occupation is given a score from 1 to 5 about how important the given trait is for the job. For example, to measure the competitiveness of an occupation, I use the measure based on the question, "To what extent does this job require the worker to compete or to be aware of competitive pressures". Each

occupation is given a score between 1 (not at all competitive), 2 (slightly competitive), 3 (moderately competitive), 4 (highly competitive) and 5 (extremely competitive). Below are the O*NET measures used in the analysis:

Competitiveness: "To what extent does this job require the worker to compete or to be aware of competitive pressures"

Social Contribution: This measure is composed of responses to the following three questions: (1) "Importance of being sensitive to others' needs and feelings and being understanding and helpful on the job", (2) "Importance of actively looking for ways to help people", (3) "Importance of providing personal assistance, medical attention, emotional support, or other personal care to others such as co-workers, customers, or patients".

The O*NET occupational data is linked with individual occupations from the ACS so the occupation in the ACS has a measure for competitiveness and social contribution. Both O*NET measures are standardized to have a mean of zero and standard deviation of 1 for the sample of all college graduates in the United States.

2.3 Sample Selection

To be included in the sample respondents of the ACS surveys from 2012-2017 must have been between the ages of 24 and 29 with at least a bachelor's degree. I apply this age restriction to analyse whether there are labour market differences between men and women with the same major at the beginning of their careers.[3] In addition, graduates must have worked full-time (35+ hours a week) (dropped 134,322) for the full year (40 weeks) (dropped 42,053) in the past year. I also restrict the sample to graduates without children (dropped 89,867). I do this as previous research has shown that men's and womens labour market

[3] I restrict the age to greater than 23 to ensure that I do not include individuals who have lower wages due to being enrolled in college for part of the 12 months, I follow Altonji et al. (2012) and restrict the age to greater than 23 as the majority of students graduate when they are 22.

experiences diverge once they have children as women take time out of the labour force and if they do return, may work fewer hours or different occupations (Blau and Kahn, 2017). The sample is also restricted to individuals with only a bachelor's degree (dropped 69,475) as I do not have information on the subject of their graduate degree. I also restrict the sample to individuals who are not enrolled in school or college (dropped 23,150) as enrolled individuals may only have the job temporarily (Joy, 2006). The sample is further restricted to graduates who earned at least half of the annual salary of a full-time minimum wage earner (dropped 2,329) as done in Denning et al. (2019) and earned less than $400,000 annually (dropped 983) to reduce the effect of outliers as done in Altonji et al. (2016b). I also dropped graduates holding the few occupations which are not covered by crosswalks between the ACS and O*NET databases (dropped 2,420). Finally I restrict the sample to individuals who majored in one of the 30 most common majors (dropped 34,575). I apply this restriction so as to have large enough sample sizes for each college major. This restriction coincides with each major have at least 1000 graduates (where at least 100 of these graduates are males or females). The 30 most common majors (out of 171 majors) covers 70% of recent college graduates. This results in a final sample size of 80,448 individuals.

2.4 Descriptive Statistics

Table 1 shows descriptive statistics for my sample and split by gender. This shows that graduates in my sample are 52% female and 48% male. The fourth column shows that women have significantly lower hourly wages than men and are in occupations with lower levels of competitiveness and inflexibility and higher levels of social contribution. However, these differences in occupational traits could originate from men and women having different college majors which lead to different types of occupations. Therefore, it is important to analyse within major gender differences which are shown in Tables 2 and 3. Table 2 shows the average hourly wage for men and women of a given college major and whether these

wages are significantly different. There are significant gender wage gaps for young, recent college graduates in 18 of the 30 majors. In 16 majors, men have higher wages than women. However, female mechanical and civil engineering graduates have significantly higher wages than male graduates. This may be due to self-selection with the highest achieving women sorting into engineering majors. Figure 1 shows these gender wage gaps along with the proportion of women in a given college major as it's important to know if gender wage gaps are found in majors with fewer women. Figure 1 does not indicate that majors with with different gender ratios are associated with larger or smaller gender wage gaps at the beginning of graduates careers. Table 3 shows the mean occupational trait by gender for graduates of a given college major and if they are significantly different. This table shows that the occupational segregation by gendered occupational traits found in Table 1 is also found when analysing graduates with the same major. It is striking that in nearly every major, men sort into more competitive and inflexible occupations while women sort into occupations with higher levels of social contribution. Table 3 is also shown graphically in Figures 2, 3 and 4.

3 Methodology

3.1 Observed Gender Wage Gap

To assess the effect on wages of occupational segregation within college major, I conduct several simulations to show the change in the average gender wage gap when equalizing occupational traits within college major. To do this, I first analyse the wages of men and women separately for each college major:

$$Wage_c^s = \beta_{c,0}^s + \mathbf{Occ}_c^s \boldsymbol{\beta}_{c,occ}^s + \mathbf{X}_c^s \boldsymbol{\beta}_{c,x}^s + \epsilon_c^s \tag{1}$$

where $Wage_c^s$ is the hourly wage of individual for males (s=m) and females (s=f); c is college major from 1 to 30; $\beta_{c,0}^s$ is the intercept; $\mathbf{Occ}_c^s$ is a vector of occupational traits (competitiveness, social contribution and inflexibility); $\mathbf{X}_c$ is a vector of demographic variables (race, potential experience, region of residence and survey year); $\boldsymbol{\beta}_{c,occ}^s$ and $\boldsymbol{\beta}_{c,x}^s$ are vectors of coefficients and ϵ_c^s is the homoscedastic, zero mean error term.

I then analyse the wages of men and women separately at their mean outcomes (denoted by overbars) for each college major:

$$\overline{Wage}_c^m = \hat{\beta}_{c,0}^m + \overline{\mathbf{Occ}}_c^m \hat{\boldsymbol{\beta}}_{c,occ}^m + \overline{\mathbf{X}}_c^m \hat{\boldsymbol{\beta}}_{c,x}^m \tag{2}$$

$$\overline{Wage}_c^f = \hat{\beta}_{c,0}^f + \overline{\mathbf{Occ}}_c^f \hat{\boldsymbol{\beta}}_{c,occ}^f + \overline{\mathbf{X}}_c^f \hat{\boldsymbol{\beta}}_{c,x}^f \tag{3}$$

where $\hat{\beta}_{c,0}^s$ is the estimated intercept and $\hat{\boldsymbol{\beta}}_{c,occ}^s$ and $\hat{\boldsymbol{\beta}}_{c,x}^s$ are vectors of estimated coefficients. The average wage for gender s in college major c is identical to the average predicted wage for gender s in college major c. The average gender wage gap for college graduates is calculated with the following equation:[4]

$$\overline{Wage}^m - \overline{Wage}^f = \sum_{c=1}^{30} \left(\frac{n_c^m}{N^m} \overline{Wage}_c^m \right) - \sum_{c=1}^{30} \left(\frac{n_c^f}{N^f} \overline{Wage}_c^f \right) \tag{4}$$

where n_c^s is the number of graduates of sex s with college major c and N^s is the total number of graduates of sex s.

[4]The simulations are done using level wages for ease of interpretation but results are robust to log transformation of wages.

3.2 Simulations

3.2.1 Equalizing Gender Representation Within Major

The first simulation that I calculate is the case where men and women are equally represented in every major. This simulation is used to show whether eliminating gender differences in college major closes the gap entirely or whether there is still a portion of the gap remaining. The simulated gender wage gap is calculated with the following equation:

$$\breve{Wage}^m - \breve{Wage}^f = \sum_{c=1}^{30} \left(\frac{(n_c^m + n_c^f)(P^m)}{N^m} \overline{Wage}_c^m \right) - \sum_{c=1}^{30} \left(\frac{(n_c^m + n_c^f)(P^f)}{N^f} \overline{Wage}_c^f \right) \quad (5)$$

where P^m and P^f are equal to the proportion of all college graduates who are male or female:

$$P^m = \frac{\sum_{c=1}^{30} n_c^m}{N^m + N^f} = \frac{N^m}{N^m + N^f} \quad (6)$$

$$P^f = \frac{\sum_{c=1}^{30} n_c^f}{N^m + N^f} = \frac{N^f}{N^m + N^f} \quad (7)$$

This simulation imposes that for each college major c, women make up P^f of the graduates and men make up P^m graduates.[5] This simulation enables me to keep the same distribution of college majors as the total graduates from a given major c remains the same and the total number of female (N^f) and male (N^m) graduates remains the same while the proportion of men and women in a given major c is allowed to change.

3.2.2 Equalizing Occupational Traits Within Major

For the second simulation, I replace

$$\overline{Wage}_c^f$$

[5] I do this instead of an equal 50/50 split of graduates for each college major to keep the total number of male and female graduates the same.

with

$$\widetilde{Wage}_c^f$$

where $\widetilde{Wage}_c^f$ is the predicted average hourly wage for female graduates for a given major when they have the same average occupational traits as men in that major. I want to do this to see what the gender wage gap for all college graduates would be if women had the same average occupational traits within a major as men. To calculate $\widetilde{Wage}_c^f$ I use the following equation:

$$\widetilde{Wage}_c^f = \beta_{0_c}^f + \overline{\mathbf{Occ}}_c^m \beta_{c,occ}^f + \overline{\mathbf{X}}_c^f \beta_{c,x}^f \tag{8}$$

where I replaced $\overline{\mathbf{Occ}}_c^f$ from Equation 3 with $\overline{\mathbf{Occ}}_c^m$ from Equation 2. When I estimate Equation 4 with $\widetilde{Wage}_c^f$ I am analyzing the gender wage gap if women have the same average occupational traits within a major as men but are compensated as women. The gender wage gap is then calculated as:

$$\overline{Wage}^m - \widetilde{Wage}^f = \sum_{c=1}^{30} \left(\frac{n_c^m}{N^m} \overline{Wage}_c^m \right) - \sum_{c=1}^{30} \left(\frac{n_c^f}{N^f} \widetilde{Wage}_c^f \right) \tag{9}$$

3.2.3 Equalizing Occupational Traits and Gender Representation Within Major

Last I do a simulation where I combine the two above simulations by female graduates having the same average occupational traits as male graduates for each college major c while the gender composition within college major is equalized:

$$\breve{Wage}^m - \grave{Wage}^f = \sum_{c=1}^{30} \left(\frac{(n_c^m + n_c^f)(P^m)}{N^m} \overline{Wage}_c^m \right) - \sum_{c=1}^{30} \left(\frac{(n_c^m + n_c^f)(P^f)}{N^f} \widetilde{Wage}_c^f \right) \tag{10}$$

3.2.4 Equal Representation in STEM Majors

In addition, as there are currently policies in the United States to increase the proportion of women in STEM majors in hopes to decrease the gender wage gap, I also conduct simulations to show the change in the gender wage gap if women are equally represented in STEM majors as men.[6] The simulated gender wage gap is calculated with the following equation:

$$Wage^m_{stem} - Wage^f_{stem} = \left[\sum_{c=1}^{STEM}\left(\frac{(n^m_c + n^f_c)(P^m)}{N^m}\overline{Wage}^m_c\right) + \sum_{c=STEM+1}^{30}\left(\frac{(n^{m,new}_{c,non})}{N^m}\overline{Wage}^m_c\right)\right] - \left[\sum_{c=1}^{STEM}\left(\frac{(n^m_c + n^f_c)(P^f)}{N^f}\overline{Wage}^f_c\right) + \sum_{c=STEM+1}^{30}\left(\frac{(n^{f,new}_{c,non})}{N^f}\overline{Wage}^f_c\right)\right] \quad (11)$$

where majors are orded so that STEM majors are associated with c=1...STEM and non-STEM majors with c=STEM+1...30 and $n^{m,new}_{c,non}$ and $n^{f,new}_{c,non}$ are defined below. This imposes that instead of equal representation of men and women in each college major as done above, I only impose equal representation of men and women in each STEM major. Each STEM major will be made up of 52% women and 48% men with the total number of male and female STEM majors begin defined as:

$$\sum_{c=1}^{STEM}(n^m_c + n^f_c)(P^m) = N^{m,new}_{STEM} \quad (12)$$

$$\sum_{c=1}^{STEM}(n^m_c + n^f_c)(P^f) = N^{f,new}_{STEM} \quad (13)$$

[6]To classify college majors in the data as STEM majors, the "STEM Designated Degree Program List" is utilized from the US Department of Homeland Security (DHS). The DHS classifies STEM majors as international students who gain a degree in a STEM field have the ability to extend their student visas after graduation. I link these STEM majors from the DHS approved list to the majors in the ACS. In this sample there are eight STEM majors: Computer Science, Computer Engineering, Mechanical Engineering, Civil Engineering, Electrical Engineering, Biology, Mathematics and Psychology.

where the original male and female STEM graduate totals were:

$$\sum_{c=1}^{STEM} n_c^m = N_{STEM}^m \tag{14}$$

$$\sum_{c=1}^{STEM} n_c^f = N_{STEM}^f \tag{15}$$

In the sample, when imposing the equal representation of genders within each STEM major, the total number of male and female STEM graduates will be different from the observed male and female STEM graduates. The difference in the total number of male and female STEM graduates is shown as follows:

$$Excess_{STEM}^m = N_{STEM}^m - N_{STEM}^{m,new} \tag{16}$$

$$Excess_{STEM}^f = N_{STEM}^f - N_{STEM}^{f,new} \tag{17}$$

As males made up more than 48% of STEM graduates in the sample, $Excess_{STEM}^m$ will be positive for men and $Excess_{STEM}^f$ will be negative for women. This means that $Excess_{STEM}^m$ of men will need to be placed in non-STEM majors and $|Excess_{STEM}^f|$ will need to be taken from non-STEM majors to be placed into STEM majors. To do this, I calculate the proportion of male (and female) graduates from each non-STEM major out of the total of non-STEM male (female) majors and place the excess males and females into each non-STEM major, c, at this proportion:

$$Excess_{c,non}^m = (Excess_{STEM}^m)\left(\frac{n_{c,non}^m}{N_{non}^m}\right) \tag{18}$$

$$Excess_{c,non}^f = \left(Excess_{STEM}^f\right)\left(\frac{n_{c,non}^f}{N_{non}^f}\right) \tag{19}$$

for each non-STEM major c where:

$$\sum_{c=STEM+1}^{30} n_{c,non}^{m} = N_{non}^{m} \tag{20}$$

$$\sum_{c=STEM+1}^{30} n_{c,non}^{f} = N_{non}^{f} \tag{21}$$

I then add the additional number of graduates to each non-STEM major:

$$n_{c,non}^{m,new} = n_{c,non}^{m} + Excess_{c,non}^{m} \tag{22}$$

$$n_{c,non}^{f,new} = n_{c,non}^{f} + Excess_{c,non}^{f} \tag{23}$$

for each non-STEM major c. As $Excess_{c,non}^{f}$ is negative, this means that I takeaway female graduates from each non-STEM major while I am adding male graduates to each non-STEM major. Finally, the new total number of male and female non-STEM graduates are:

$$\sum_{c=STEM+1}^{30} n_{c,non}^{m,new} = N_{non}^{m,new} \tag{24}$$

$$\sum_{c=STEM+1}^{30} n_{c,non}^{f,new} = N_{non}^{f,new} \tag{25}$$

With this simulation, I am able to keep the total number of STEM and non-STEM graduates the same as:

$$N_{non}^{m,new} + N_{non}^{f,new} = N_{non} \tag{26}$$

and

$$N_{STEM}^{m,new} + N_{STEM}^{f,new} = N_{STEM} \tag{27}$$

while also keeping the total number of female and male graduates the same:

$$N_{STEM}^{m,new} + N_{non}^{m,new} = N^{m} \tag{28}$$

and

$$N_{STEM}^{f,new} + N_{non}^{f,new} = N^f \tag{29}$$

3.2.5 Equal Representation in STEM Majors and Equalizing Occupational Traits

This last simulation calculates the gender wage gap if there is equal representation of gender within each STEM major and female STEM graduates have the same average occupational traits as male STEM graduates:

$$\begin{aligned} Wage_{stem}^{m} - \widetilde{Wage}_{stem}^{f} = \\ \left[\sum_{c=1}^{STEM}\left(\frac{(n_c^m + n_c^f)(P^m)}{N^m}\overline{Wage}_c^m\right) + \sum_{c=STEM+1}^{30}\left(\frac{(n_{c,non}^{m,new})}{N^m}\overline{Wage}_c^m\right)\right] - \\ \left[\sum_{c=1}^{STEM}\left(\frac{(n_c^m + n_c^f)(P^f)}{N^f}\widetilde{Wage}_c^f\right) + \sum_{c=STEM+1}^{30}\left(\frac{(n_{c,non}^{f,new})}{N^f}\overline{Wage}_c^f\right)\right] \end{aligned} \tag{30}$$

This will show whether it is important in a policy which increases the representation of women in STEM majors to also try to decrease occupational segregation within STEM majors.

4 Results

4.1 OLS Estimations

Figures 5, 6 and 7 shows the OLS estimations of female and male wages from Equation 1.[7] Figure 5 shows the beta coefficients for competitiveness of an occupation for a given college major and if they are significantly different from zero. For example, a one standard

[7]Standard errors are clustered at the occupational level as occupational traits are measured at the occupational level.

deviation increase in the competitiveness of an occupation is associated with approximately a $2 increase in one's hourly wage for business majors holding all other covariates constant. On average theses figures show that being in an occupations with higher levels of competitiveness or inflexibility is associated with higher wages while being in an occupation with higher levels of social contribution is associated with lower wages. It is also interesting to see that the returns to these occupational traits seem to follow similar patterns for both male and female graduates. These figures show the OLS estimation results which are used in the simulations in the next section. In the next section I will show how the gender wage gap changes when female graduates have the same average average occupational traits within major as male graduates.

4.2 Simulations

4.2.1 Overall Simulations

Table 4a shows what happens to the hourly gender wage gap under different simulations. The first column, Actual, shows the observed average male and female wage and the resulting average wage gap (as shown in Equation 4). Wage Gap (%) is calculated by taking the female wage minus the male wage, divided the male wage. This shows in the sample that there is a 13.49% gender wage gap for young graduates without children. This gender wage may be the result of occupational segregation within major or men and women choosing different college majors which lead to different occupations. By conducting simulations separately equalizing gender representation within each college major and equalizing occupational traits within major, I can gain a better understanding of why this gender wage gap exists.

The second column, Equal Representation in Every Major, shows the simulated gender wage gap if the gender composition of each major was approximately equal (as shown in Equation 5). With this simulation both the average male and female wages change as I am

changing the number of male and female graduates within each college major. By imposing this 'equal representation' within college major, the average male wage decreases from \$24.17 to \$23.03 as male graduates have majors associated with higher wages while the average female wage increases from \$20.91 to \$22.00 as female graduates have majors associated with lower wages. The gender wage decreases from \$3.26 to \$1.03 which results in a 68.54% reduction in the gender wage gap.[8] This shows that eliminating gender differences in college major has a large impact on the gender wage gap; however, it also shows that approximately 32% of the gender wage gap still remains once accounting for gender differences in college major. This indicates that there may be gender differences in returns to college major.

The third column, Equalized Traits, answers whether occupational segregation by gendered occupational traits within college major is a reason for gender differences in returns to college major. Equalized Traits shows the simulated gender wage gap if female graduates have the same average occupational traits within major as male graduates (as shown in Equations 8 and 9). The average male wage stays the same as the actual male wage while the female wage increases from \$20.91 to \$21.45 as a result of the female graduates now having the same average occupational traits within major as men. The gender wage gap decreases from \$3.26 to \$2.72 which results in a 16.68% reduction in the gender wage gap. This indicates that there are gender differences in returns to college major due to occupational segregation of gendered occupational traits.

It is important to see if it is possible to account for the entire gender wage gap; therefore, the fourth column, Equalize Traits and Major, combines the previous two simulations and simulates the gender wage gap if female graduates have the same average occupational traits within major as male graduates and there is equal gender representation within each college major (as shown in Equation 10). This simulation results in a decrease of the gender wage gap from \$3.26 to \$0.41 which is a 87.55% reduction in the gender wage gap. This in-

[8]This is calculated by taking the simulated gender wage gap minus the actual gender wage gap with the difference divided by the actual gender wage gap.

dicates that once one accounts for gender differences in occupational traits within major and gender differences in college major, there is only a small gender wage gap remaining (1.76%.) for young, recent college graduates. Therefore, it is important for policies to not only target moving women into higher paying majors but to also attempt to decrease occupational segregation within major.

Table 4b shows the same simulation results as in Table 4a; however, instead of using female specific returns to occupational traits (as shown in Equation 8) I impute male specific returns to occupational traits. I do this as it could be argued that young women may receive the same return to occupational traits if they are in the exact same occupations as men. Table 4b shows very similar results to Table 4a indicating that there are not large gender differences in returns to occupational traits (as was already seen in Figures 5, 6 and 7).

4.2.2 STEM Simulations

Currently, there are policies in the United States to increase the proportion of female STEM graduates as they are underrepresented in STEM fields which typically have large financial returns. Therefore, I conduct simulations which analyze whether these policies are effective by analysing how much of the gender wage gap could reduce if men and women are equally represented in STEM majors. Table 5 shows the simulations focusing on STEM majors. The first column (Actual) is the same as shown in Table 4a and 4b. The second column, Equal Representation in STEM Majors, shows the simulated gender wage gap if the gender composition in each STEM major is approximately equal (as shown in Equation 11). This results in a decrease in the average male wage from \$24.17 to \$23.12 and an increase in the average female wage from \$20.91 to \$21.97. The gender wage gap decreases to \$1.15 with a reduction in the gender wage gap of 64.74%. This is an interesting result as the reduction in the gender wage gap from having equal representation in all majors from Table 4a was

68.54%. This indicates that the majority of this reduction is due to more women going into STEM majors which indicates that policies to increase the proportion of female STEM majors are well founded. It is vital for policy makers to understand if policies should target a defined group of majors or all majors as resources can be better utilized to have the largest impact.[9]

The third column, Equalize Traits in STEM, shows the simulated gender wage gap if women have the same average occupational traits within STEM majors as men. This results in a reduction of the gender wage gap by 4.06%. At first glance this may seem small compared to the results in Table 4a (16.68% reduction) however, it is important to keep in mind that this reduction only comes from equalizing occupational traits within eight majors instead of thirty majors as in Table 4a. These results indicate that occupational segregation by gendered occupational traits does occur in STEM majors; however, it doesn't seem to be large. The fourth column, Equalize Traits and Major in STEM, shows the simulated gender wage gap if female STEM graduates have the same average occupational traits within STEM major as male STEM graduates and if the gender composition in each STEM major is approximately equal (as shown in Equation 30). This results in a 69.27% reduction in the gender wage gap. This shows that if policies only target STEM majors, that 30% of the gender wage gap for young graduates will still exist. This shows the importance of also targeting non-STEM majors in policies.

4.3 Decompositions

This section seeks to gain more understanding for why there is a decrease in the gender wage gap when female graduates have the same average occupational traits as male graduates for each college major. To do this, Table 6 shows multiple decompositions of the gender

[9]For this sample, that means a policy only targeting 8 majors instead of 30 majors.

wage gaps within college major.[10] I use these decompositions to show that there are gender differences in occupational traits and that these differences are significantly related to wages. Table 6 shows the hourly gender wage gap for different college majors (which matches the gender wage gaps shown in Table 2). For brevity, Table 6 only shows the gender wage gap decompositions of college majors where the total contribution of occupational traits has significant wage associations. The Explained row shows how much of the gender wage gap can be explained by gender differences in occupational traits and demographic variables. **Occ Traits** shows the summed contribution of the occupational traits to the gender wage gap and **Other Demo** is the summed contribution of all demographic variables. The individual contribution of the occupational traits is also shown. Unexplained shows what portion of the gender wage gap cannot be accounted.

Table 6 shows that in 18 out of the 30 most popular majors, there are significant gender differences in occupational traits which are significantly associated with wages. The only major with significant gender differences in all occupational traits was Business. This possibly indicates that there are many potential occupations for business graduates and therefore occupational segregation is prevalent. Majors with significant gender differences in both competitiveness and inflexibility are: Psychology, English, Biology, Finance, Economics and History majors. There are significant gender differences in competitiveness and social contribution for Mathematics graduates. Marketing and Liberal Arts graduates have significant gender differences in competitiveness while Criminal Justice, Political Science, Parks and Recreation and Sociology graduates have significant gender differences in inflexibility of occupations.

[10]The methodology for the decompositions performed in Table 6 are shown in the Appendix.

4.4 College Majors Without Gender Differences in Occupational Traits

Table 6 shows gender wage decompositions within majors; however, there were not significant occupational differences which were associated with wages in 12 majors. It is important to understand why these majors do not have gender differences in occupational traits. There is a set of literature which finds that some college majors are closely related to a few occupations in the labour market (Accounting, Engineering, Nursing, etc.) while other majors lead to a plethora of occupational choices (Business, Economics, etc.) (Altonji et al., 2016b, 2012; Ransom and Phipps, 2017; Arcidiacono et al., 2014). Joy (2006, 2000) stated that the potential for occupational segregation within college major is greater for majors which lead to a lot of potential occupations compared to majors with only a few potential occupations. Figure 8 provides support for this theory. Figure 8 shows the percentage of graduates from each major who are found in the top five most common occupations for that given major.[11] The higher the percentage of graduates in a top five occupation, the less likely it is that one would find significant gender differences in occupational traits. The white (grey) bars indicate college majors that did (not) have gender differences in occupational traits which were associated with wages. It is easy to see that majors without gender differences in occupational traits contributing to wages are also the majors with the highest concentration of graduates in the most common occupations for the major. One outlier is Computer Science where there is a high concentration of graduates in the top five occupations; however, gender differences in occupational traits for these graduates do contribute to wages. Therefore, it does seem to be the case that if a college major does not prepare a graduate for a specific type of occupation, then it is reasonable to assume that occupational segregation within major may exist.

[11] This analysis was also done in Altonji et al. (2016b).

5 Sensitivity Analysis

5.1 Simulations

The results for the simulations are robust to changing the dependent variable. Table 7 shows that the results remain when using log hourly wages instead of level hourly wages. Table 8 shows the simulation results when using annual income instead of hourly wages. Table 8 Column 2 (Equal Representation in Every Major) shows that the gender wage gap decreases by 61.79% compared to 68.54% when analysing hourly wages. In addition, equalizing traits within major decreases the gender wage gap by 13.37% compared to 16.68% when using hourly wages. The differences between the simulations using different dependent variables are potentially due to the fact that within each college major, women tend to work fewer hours a week than men (even though they are working full-time). This can be seen in the fourth column where I equalize traits and weekly hours within college major. This results in a 22.95% reduction in the gender wage gap. The sixth column (Equalize Traits, Weekly Hours and Major) shows very similar to results as in Table 4a column 4. When equalizing traits and weekly hours within major along with equal representation within major, the gender wage gap reduces by 88.17% compared to 87.55% in Table 4a. Table 9 shows the simulation results if I only change the average female occupational traits in majors to the average male occupational traits in majors if gender differences in occupational traits significantly contributed to wages (as shown in Table 6). The results remain very similar to Table 4a. This indicates that when creating policies to decrease occupational segregation within major, that one only needs to target specific majors such as the majors in Table 6 because reducing occupational segregation in majors where occupational segregation doesn't contribute to a gender wage gap doesn't have a large effect on wages.

Tables 10a, 10b and 10c show that the results are robust to expanding the sample to include individual with children and work part-time, who are still enrolled in school and

individuals with more than a bachelor's degree. The results for equalizing traits within major for these three different samples remain very similar to those found in the main result. However, the effect of having equal representation in every major can be slightly different based on the sample used. In Table 10a which expands the sample to include individuals with children and who work part-time, eliminating gender differences in college major reduces the gender wage gap by 60.88% compared to 68.54% in the main sample. In addition, in the fourth column (Equalize Traits and Major) there is only a 80.47% reduction in the gap compared to 87.55% in Table 4a. Due to data limitations, I am only able to control for potential experience; therefore, the larger remaining gender wage gap compared to Table 4a could be due to women with children having less experience which is not controlled for in this sample. Table 10c includes individuals with more than a bachelors degree (while controlling for whether they have a higher degree). The second column shows that having equal representation in every major reduces the gap by 80.53% compared to 68.54% in Table 4a. This stronger result may be due to women shifting into majors which are associated with significantly higher wages if one gains a further degree.

5.2 Decompositions

Decompositions require the choice of a reference group. As shown in Equation 40 in the Appendix, men are chosen as the reference group in the main analysis. It is common in the gender wage gap literature to use men as the reference group as it is assumed, in a world without discrimination, women would be compensated the same as men with similar characteristics. However, the choice of the reference group may have an effect on the results so it is important to analyse whether the results hold if the counterfactual changes. I do the same analysis as shown in Table 6 in Table 11 using women as the reference group. Table 11 shows that the decomposition results remain when using the female wage structure as the reference wage.

6 Conclusion

This paper shows evidence of occupational segregation by gendered occupational traits within college major for a sample of young college graduates at the beginnings of their careers. This paper simulates changes in the gender wage gap of recent college graduates if female graduates had the same average occupational traits within majors as male graduates. I find that men and women with the same level and type of education follow gender norms with men attaining more competitive and inflexible occupations while women attain occupations with higher levels of social contribution. These gender differences are found in a sample of young men and women at the beginnings of their careers and will most likely increase as they age. In addition, this paper finds that when women have the same average occupational traits within major as men and men and women are equally represented in each major, that the gender wage gap of young college graduates is nearly eliminated. Therefore, policies to decrease the gender wage gap of college graduates could attempt to decrease occupational segregation within college major. This could be done by educating young women about the wage implications of forgoing competitive and inflexible at the beginnings of their careers. However, if men and women are sorting into occupations based on their actual preferences, it may not be efficient to push them into occupations that they do not prefer. If the ultimate goal of policy makers is to decrease the gender wage gap, it may be better to create more flexible work arrangements for certain occupations so they attract more women and to compensate occupations which contribute to society.

Furthermore, this paper finds that the majority of the reduction in the gender wage gap when men and women are in the same majors comes from the increasing number of women in STEM majors. Therefore, policies should continue to encourage women to major in STEM fields. However, it is important to note that encouraging women into different college majors could potentially result in larger occupational segregation within major if these new women are not as enthusiastic as the women who did not require additional incentives to

pick that major. Going forward, it will be important to analyse if policies which attempt to increase the number of female graduates in specific majors results in female graduates attaining the same types of occupations as male graduates.

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Table 1: Overall Descriptive Statistics

VARIABLES	1 Total	2 Female	3 Male	4 Diff
Hourly Wage (2017 US $'s)	22.46	20.91	24.17	***
	(11.25)	(9.69)	(12.52)	
Female	0.52			
	(0.50)			
Competitiveness of occ (z)	0.06	-0.13	0.27	***
	(1.00)	(1.00)	(0.95)	
Social Contribution of occ (z)	0.01	0.30	-0.31	***
	(1.02)	(1.04)	(0.88)	
Inflexibility of occ (z)	-0.01	-0.23	0.23	***
	(0.98)	(0.98)	(0.91)	
Non-white	0.18	0.17	0.18	**
	(0.38)	(0.38)	(0.38)	
Potential Experience	4.48	4.39	4.59	***
	(1.67)	(1.67)	(1.66)	
New England	0.06	0.06	0.07	***
	(0.25)	(0.24)	(0.25)	
Mid-Atlantic	0.17	0.16	0.17	***
	(0.37)	(0.37)	(0.38)	
East North Central	0.15	0.15	0.15	*
	(0.36)	(0.36)	(0.36)	
West North Central	0.06	0.06	0.06	**
	(0.24)	(0.24)	(0.24)	
South Atlantic	0.19	0.20	0.18	***
	(0.39)	(0.40)	(0.38)	
East South Central	0.04	0.05	0.04	***
	(0.20)	(0.21)	(0.20)	
West South Central	0.10	0.10	0.10	
	(0.30)	(0.31)	(0.30)	
Mountain	0.06	0.06	0.06	
	(0.23)	(0.23)	(0.23)	
Pacific	0.16	0.16	0.16	
	(0.37)	(0.37)	(0.37)	
2012 Survey	0.15	0.15	0.15	
	(0.35)	(0.35)	(0.35)	
2013 Survey	0.16	0.16	0.16	**
	(0.37)	(0.37)	(0.36)	
2014 Survey	0.16	0.16	0.16	
	(0.36)	(0.36)	(0.37)	
2015 Survey	0.17	0.17	0.17	
	(0.38)	(0.38)	(0.38)	
2016 Survey	0.18	0.18	0.18	
	(0.38)	(0.38)	(0.38)	
2017 Survey	0.19	0.18	0.19	
	(0.39)	(0.39)	(0.39)	
Observations	80,448	42,013	38,435	

Notes: Mean and standard deviations in parentheses. Occupational traits are standardized to (0,1) for the entire college graduate sample. Diff column indicates whether t-test difference in means was significant. Potential Experience is age minus 22. The sample is restricted to individuals aged 24-29 who are employed full-time, full year who have no children, only one college major, no degree above a bachelor's degree, not currently enrolled in school and have a bachelor's degree from a Top 30 major. Wages are restricted to individuals who made between $7,000 and $400,000 annually as done in previous research.

Table 2: Descriptive Statistics of Wages by College Major

	Female		Male			
College Major	**Mean Wage**	**sd**	**Mean Wage**	**sd**	**Difference**	**N**
Business	21.26	10.25	23.03	11.51	1.77***	10973
Nursing	28.13	8.96	29.41	10.26	1.28***	5270
Psychology	17.43	7.72	18.99	11.42	1.56***	4658
Marketing	21.67	9.09	23.29	11.18	1.63***	4581
Communications	20.45	8.54	21.00	11.78	0.55	4391
Finance	26.35	12.20	27.55	13.85	1.20**	3292
Accounting	23.71	8.72	23.84	9.87	0.13	3285
Criminal Justice	17.71	6.91	20.21	8.67	2.50***	3258
Computer Science	31.51	15.62	33.55	15.86	2.04**	3073
Elementary Education	15.84	5.02	16.35	5.48	0.51	2853
English	18.08	8.17	18.18	8.68	0.10	2766
Mechanical Engineering	31.96	9.46	30.47	9.18	-1.49**	2684
Graphic Design	19.43	8.25	20.41	9.55	0.98**	2628
Biology	17.93	7.90	18.90	9.87	0.97***	2595
Economics	26.97	12.81	27.27	14.27	0.30	2301
Political Science	21.01	9.54	21.93	11.43	0.92**	2254
Parks and Rec	16.51	7.25	18.05	8.58	1.54***	2098
History	18.37	9.14	19.01	9.62	0.64	1962
General Education	16.94	5.50	18.09	12.41	1.15*	1733
Sociology	18.11	9.09	19.49	10.33	1.38***	1707
Journalism	19.71	8.72	19.14	8.85	-0.57	1469
Electrical Engineering	33.04	11.58	32.59	11.56	-0.45	1378
Civil Engineering	27.98	8.54	26.76	8.19	-1.18**	1359
Fine Arts	16.63	7.84	17.70	8.56	1.07**	1236
Hospitality Management	17.78	7.00	18.28	8.36	0.50	1224
Advertising	21.32	9.20	22.58	14.27	1.26	1172
Liberal Arts	16.92	7.20	19.33	13.00	2.41***	1119
Mass Media	18.80	8.18	18.69	9.35	-0.11	1075
Mathematics	24.68	11.82	26.68	14.61	2.00**	1031
Computer Engineering	34.85	14.85	35.78	14.66	0.93	1023

Notes: Data from ACS. Hourly wage calculated in 2017 US dollars. Difference indicates whether t-test difference in means was significant. The sample is restricted to individuals aged 24-29 who are employed full-time, full year who have no children, only one college major, no degree above a bachelor's degree, not currently enrolled in school and have a bachelor's degree from a Top 30 major. Wages are restricted to individuals who made between $7,000 and $400,000 annually as done in previous research. *** p<0.01, ** p<0.05, * p<0.10.

Table 3: Mean Occupational Traits by College Major

	Mean Competitiveness			Mean Social Contribution			Mean Inflexibility		
College Major	**Female**	**Male**	**Diff**	**Female**	**Male**	**Diff**	**Female**	**Male**	**Diff**
Business	0.04	0.35	***	-0.03	-0.21	***	0.02	0.33	***
Nursing	-0.38	-0.40		2.05	1.99	***	-1.13	-1.10	*
Psychology	-0.47	-0.16	***	0.50	0.23	***	-0.42	-0.13	***
Marketing	0.34	0.53	***	-0.08	-0.23	***	0.16	0.32	***
Communications	0.13	0.29	***	0.04	-0.16	***	-0.03	0.10	***
Finance	0.38	0.68	***	-0.38	-0.44	**	0.20	0.42	***
Accounting	0.37	0.45	***	-0.58	-0.59		0.03	0.14	***
Criminal Justice	-0.56	-0.31	***	0.36	0.31		-0.22	0.27	***
Computer Science	0.60	0.64		-0.88	-1.04	***	0.22	0.27	*
Elementary Education	-1.11	-0.90	***	0.88	0.71	***	-0.19	-0.02	***
English	-0.22	-0.04	***	0.08	-0.10	***	-0.28	-0.15	***
Mechanical Engineering	0.29	0.35	*	-0.95	-0.94		0.74	0.72	
Graphic Design	0.42	0.39		-0.55	-0.68	***	-0.25	-0.14	***
Biology	-0.40	-0.21	***	0.07	-0.17	***	-0.32	0.00	***
Economics	0.34	0.53	***	-0.29	-0.38	**	0.19	0.37	***
Political Science	-0.01	0.14	***	0.00	-0.09	**	-0.08	0.16	***
Parks and Rec	-0.31	0.02	***	0.59	0.22	***	-0.52	-0.06	***
History	-0.28	-0.07	***	0.19	0.00	***	-0.31	0.09	***
General Education	-0.97	-0.68	***	0.82	0.55	***	-0.16	0.09	***
Sociology	-0.38	-0.09	***	0.48	0.19	***	-0.39	0.03	***
Journalism	0.48	0.64	***	-0.27	-0.51	***	0.09	0.14	
Electrical Engineering	0.39	0.29	**	-0.93	-0.93		0.44	0.50	*
Civil Engineering	0.39	0.47	**	-0.84	-0.86		0.51	0.65	***
Fine Arts	-0.06	0.09	**	-0.13	-0.47	***	-0.43	-0.15	***
Hospitality Management	0.08	0.27	***	0.36	0.24	**	-0.06	0.37	***
Advertising	0.33	0.42		-0.04	-0.22	***	0.10	0.12	
Liberal Arts	-0.50	0.00	***	0.38	-0.10	***	-0.45	0.05	***
Mass Media	0.30	0.23		-0.26	-0.39	***	0.06	0.03	
Mathematics	0.02	0.28	***	-0.14	-0.58	***	0.15	0.21	
Computer Engineering	0.69	0.71		-0.99	-1.08		0.35	0.35	

Notes: Data from ACS and O*NET. Same sample sizes as in Table 2. Occupational traits are standardized to (0,1) for the entire college graduate sample. Diff indicates whether a t-test of difference in means for females and males is statistically significant. The sample is restricted to individuals aged 24-29 who are employed full-time, full year who have no children, only one college major, no degree above a bachelor's degree, not currently enrolled in school and have a bachelor's degree from a Top 30 major. Wages are restricted to individuals who made between $7,000 and $400,000 annually as done in previous research.

Table 4a: Simulations of Hourly Gender Wage Gap ($'s)

	Actual	Equal Representation in Every Major	Equalize Traits	Equalize Traits and Major
Male Wage	24.17	23.03	24.17	23.03
Female Wage	20.91	22.00	21.45	22.62
Wage Gap	3.26	1.03	2.72	0.41
Wage Gap (%)	13.49%	4.46%	11.24%	1.76%
Reduction in Gap		**-68.54%**	**-16.68%**	**-87.55%**
Male Sample	38435	38435	38435	38435
Female Sample	42013	42013	42013	42013

*Notes: Data from ACS and O*NET. Actual is the unsimulated gender wage gap. Equal Representation in Every Major shows the gender wage gap when every major has a gender composition of 52% female and 48% male. Equalized Traits shows the gender wage gap if females have the same average occupational traits within college major as men. Equalize Traits and Major shows the gender wage gap when females have the same average occupational traits within college major as men and every major has a gender composition of 52% female and 48% male. The sample is restricted to individuals aged 24-29 who are employed full-time, full year who have no children, only one college major, no degree above a bachelor's degree, not currently enrolled in school and have a bachelor's degree from a Top 30 major. Wages are restricted to individuals who made between $7,000 and $400,000 annually as done in previous research.

Table 4b: Simulations of Hourly Gender Wage Gap ($'s) with Male Coefficients

	Actual	Equal Representation in Every Major	Equalize Traits	Equalize Traits and Major
Male Wage	24.17	23.03	24.17	23.03
Female Wage	20.91	22.00	21.46	22.64
Wage Gap	3.26	1.03	2.71	0.39
Wage Gap (%)	13.49%	4.46%	11.22%	1.69%
Reduction in Gap		**-68.54%**	**-17.01%**	**-88.19%**
Male Sample	38435	38435	38435	38435
Female Sample	42013	42013	42013	42013

*Notes: Data from ACS and O*NET. Uses male returns to occupational traits instead of female returns as shown in Equation (4). Actual is the unsimulated gender wage gap. Equal Representation in Every Major shows the gender wage gap when every major has a gender composition of 52% female and 48% male. Equalized Traits shows the gender wage gap if females have the same average occupational traits within college major as men. Equalize Traits and Major shows the gender wage gap when females have the same average occupational traits within college major as men and every major has a gender composition of 52% female and 48% male. The sample is restricted to individuals aged 24-29 who are employed full-time, full year who have no children, only one college major, no degree above a bachelor's degree, not currently enrolled in school and have a bachelor's degree from a Top 30 major. Wages are restricted to individuals who made between $7,000 and $400,000 annually as done in previous research.

Table 5: Simulations of Hourly Gender Wage Gap ($'s) STEM Majors

	Actual	Equal Representation in STEM	Equalize Traits in STEM	Equalize Traits and Major in STEM
Male Wage	24.17	23.12	24.17	23.12
Female Wage	20.91	21.97	21.04	22.12
Wage Gap	3.26	1.15	3.13	1.00
Wage Gap (%)	13.49%	4.97%	12.95%	4.33%
Reduction in Gap		**-64.74%**	**-4.06%**	**-69.27%**
Male Sample	38435	38435	38435	38435
Female Sample	42013	42013	42013	42013

*Notes: Data from ACS and O*NET. Actual is the unsimulated gender wage gap. Equal Representation in STEM shows the gender wage gap when every STEM major has a gender composition of 52% female and 48% male. Equalized Traits in STEM shows the gender wage gap if females have the same average occupational traits within STEM major as men. Equalize Traits and Major in STEM shows the gender wage gap when females have the same average occupational traits within STEM major as men and every STEM major has a gender composition of 52% female and 48% male. The sample is restricted to individuals aged 24-29 who are employed full-time, full year who have no children, only one college major, no degree above a bachelor's degree, not currently enrolled in school and have a bachelor's degree from a Top 30 major. Wages are restricted to individuals who made between $7,000 and $400,000 annually as done in previous research.

Table 6: Decompositions of Gender Wage Gaps Within College Major

	Business	Psychology	Marketing	Computer Science	Communications	Criminal Justice
Wage Gap	1.77***	1.56***	1.63***	2.04***	0.56	2.50***
Explained	1.14***	1.40***	0.75***	0.40	0.92**	0.96**
Occ Traits	1.09***	1.09***	0.55**	1.03***	0.61*	0.84**
Competitiveness	0.67***	0.53***	0.39**	0.23	0.22	0.09
Contribution	0.19**	0.12	0.07	0.66**	0.17	-0.04
Inflexibility	0.12**	0.44***	0.09	0.14	0.22	0.79**
Other Demo	0.06	0.30**	0.19	-0.63	0.31*	0.12
Unexplained	0.62**	0.16	0.88***	1.63**	-0.36	1.54***

	English	Biology	Finance	Economics	Political Science	Parks and Rec
Wage Gap	0.10	0.97**	1.21**	0.30	0.93*	1.54***
Explained	0.69***	0.85***	1.22***	0.88***	0.68**	1.17***
Occ Traits	0.52**	0.75***	1.10***	0.91***	0.71**	0.74***
Competitiveness	0.22**	0.34**	0.63***	0.50**	0.26	0.21
Contribution	0.12	-0.05	0.06	0.15	0.08	0.22
Inflexibility	0.18*	0.45**	0.41***	0.26**	0.36**	0.31**
Other Demo	0.17	0.10	0.11	-0.03	-0.02	0.43***
Unexplained	-0.59*	0.12	-0.01	-0.58	0.24	0.37

	History	Sociology	Fine arts	Hospital Management	Liberal Arts	Mathematics
Wage Gap	0.60	1.38*	1.07	0.50	2.41***	2.00**
Explained	1.15***	1.33***	0.93**	0.88**	1.52***	2.84***
Occ Traits	1.06***	1.23***	0.75**	0.61*	1.27***	2.93***
Competitiveness	0.27*	0.30	0.31	0.16	1.05***	0.99**
Contribution	0.14	0.01	0.28	0.07	0.27	1.18***
Inflexibility	0.65***	0.92**	0.16	0.38	-0.05	0.09
Other Demo	0.09	0.09	0.18	0.26	0.25	-0.09
Unexplained	-0.54	0.05	0.14	-0.37	0.89	-0.84

*Notes: Data from ACS and O*NET. Standard errors are clustered at the occupational level but not shown for brevity. *** p<0.01, ** p<0.05, * p<0.10. This table shows O-B decompositions of within major hourly gender wage gaps. This table only shows the college majors where gender differences in occupational traits were a significant contributor to the gender wage gap. **Occ Traits** is the summed contribution of the individual occupational traits. **Other Demo** is the summed contribution of all demographic variables. The sample is restricted to individuals aged 24-29 who are employed full-time, full year who have no children, only one college major, no degree above a bachelor's degree and not currently enrolled in school. Wages are restricted to individuals who made between $7,000 and $400,000 annually as done in previous research.

Table 7: Simulations of Log Hourly Gender Wage Gap ($'s)

	Actual	Equalized Traits	Equal Representation in Every Major	Equalize Traits and Major
Male Wage	3.07	3.07	3.02	3.02
Female Wage	2.94	2.97	2.98	3.01
Wage Gap	0.13	0.10	0.03	0.01
Male Sample	38435	38435	38435	38435
Female Sample	42013	42013	42013	42013

*Notes: Data from ACS and O*NET. Actual is the unsimulated gender wage gap. Equal Representation in Every Major shows the gender wage gap when every major has a gender composition of 52% female and 48% male. Equalized Traits shows the gender wage gap if females have the same average occupational traits within college major as men. Equalize Traits and Major shows the gender wage gap when females have the same average occupational traits within college major as men and every major has a gender composition of 52% female and 48% male. The sample is restricted to individuals aged 24-29 who are employed full-time, full year who have no children, only one college major, no degree above a bachelor's degree, not currently enrolled in school and have a bachelor's degree from a Top 30 major. Wages are restricted to individuals who made between $7,000 and $400,000 annually as done in previous research.

Table 8: Simulations of Annual Gender Income Gap ($'s)

	Actual	Equal Representation in Every Major	Equalized Traits	Equalized Traits and Weekly Hours	Equalize Traits and Major	Equalize Traits, Weekly Hours and Major
Male Income	55264	52211	55264	55264	52211	52211
Female Income	45831	48607	47092	47996	50015	51084
Income Gap	9433	3604	8172	7268	2196	1116
Income Gap (%)	17.07%	6.90%	14.79%	13.15%	4.21%	2.14%
Reduction in Gap		**-61.79%**	**-13.37%**	**-22.95%**	**-76.72%**	**-88.17%**
Male Sample	38435	38435	38435	38435	38435	38435
Female Sample	42013	42013	42013	42013	42013	42013

*Notes: Data from ACS and O*NET. Actual is the unsimulated gender income gap. Equalized Traits shows the gender wage gap if females have the same average occupational traits within college major as men. Equalized Traits and Weekly Hours shows the gender wage gap if females have the same average occupational traits and weekly hours within college major. Equal Representation in Every Major shows the gender wage gap when every major has a gender composition of 52% female and 48% male. Equalize Traits and Major shows the gender wage gap when females have the same average occupational traits within college major as men and every major has a gender composition of 52% female and 48% male. Equalize Traits and Major shows the gender wage gap when females have the same average occupational traits and weekly hours within college major as men and every major has a gender composition of 52% female and 48% male. The sample is restricted to individuals aged 24-29 who are employed full-time, full year who have no children, only one college major, no degree above a bachelor's degree, not currently enrolled in school and have a bachelor's degree from a Top 30 major. Wages are restricted to individuals who made between $7,000 and $400,000 annually as done in previous research.

Table 9: Simulations of Hourly Gender Wage Gap ($'s) Only Change Traits in Majors with Significantly Different Occupational Traits in Decompositions

	Actual	Equal Representation in Every Major	Equalize Traits	Equalize Traits and Major
Male Wage	24.17	23.03	24.17	23.03
Female Wage	20.91	22.00	21.42	22.58
Wage Gap	3.26	1.03	2.75	0.45
Wage Gap (%)	13.49%	4.46%	11.37%	1.94%
Reduction in Gap		**-68.54%**	**-15.76%**	**-86.33%**
Male Sample	38435	38435	38435	38435
Female Sample	42013	42013	42013	42013

*Notes: Data from ACS and O*NET. Actual is the unsimulated gender wage gap. Equal Representation in Every Major shows the gender wage gap when every major has a gender composition of 52% female and 48% male. Equalized Traits shows the gender wage gap if females have the same average occupational traits within college major as men only for college majors found in Table 6. Equalize Traits and Major shows the gender wage gap when females have the same average occupational traits within college major as men for college majors found in Table 6 and every major has a gender composition of 52% female and 48% male. The sample is restricted to individuals aged 24-29 who are employed full-time, full year who have no children, only one college major, no degree above a bachelor's degree, not currently enrolled in school and have a bachelor's degree from a Top 30 major. Wages are restricted to individuals who made between $7,000 and $400,000 annually as done in previous research.

Table 10a: Simulations of Hourly Gender Wage Gap ($'s) Including Individuals with Children and Working Part-time

	Actual	Equal Representation in Every Major	Equalize Traits	Equalize Traits and Major
Male Wage	23.97	22.87	23.97	22.87
Female Wage	20.66	21.58	21.21	22.23
Wage Gap	3.31	1.29	2.76	0.64
Wage Gap (%)	13.78%	5.65%	11.49%	2.82%
Reduction in Gap		**-60.88%**	**-16.62%**	**-80.47%**
Male Sample	38435	38435	38435	38435
Female Sample	42013	42013	42013	42013

*Notes: Data from ACS and O*NET. The sample is expanded to include individuals with children or work part-time (at least 20 hours a week). Actual is the unsimulated gender wage gap. Equal Representation in Every Major shows the gender wage gap when every major has a gender composition of 52% female and 48% male. Equalized Traits shows the gender wage gap if females have the same average occupational traits within college major as men. Equalize Traits and Major shows the gender wage gap when females have the same average occupational traits within college major as men and every major has a gender composition of 52% female and 48% male. The sample is restricted to individuals aged 24-29 who are employed full year, only one college major, no degree above a bachelor's degree, not currently enrolled in school and have a bachelor's degree from a Top 30 major. Wages are restricted to individuals who made between $7,000 and $400,000 annually as done in previous research.

Table 10b: Simulations of Hourly Gender Wage Gap ($'s)
Including Individuals Still Enrolled in School

	Actual	Equal Representation in Every Major	Equalize Traits	Equalize Traits and Major
Male Wage	23.81	22.68	23.81	22.68
Female Wage	20.69	21.73	21.23	22.33
Wage Gap	3.12	0.96	2.59	0.35
Wage Gap (%)	13.11%	4.22%	10.86%	1.54%
Reduction in Gap		**-69.30%**	**-17.11%**	**-88.78%**
Male Sample	38435	38435	38435	38435
Female Sample	42013	42013	42013	42013

*Notes: Data from ACS and O*NET. Actual is the unsimulated gender wage gap. Equal Representation in Every Major shows the gender wage gap when every major has a gender composition of 52% female and 48% male. Equalized Traits shows the gender wage gap if females have the same average occupational traits within college major as men. Equalize Traits and Major shows the gender wage gap when females have the same average occupational traits within college major as men and every major has a gender composition of 52% female and 48% male. The sample is restricted to individuals aged 24-29 who are employed full-time, full year who have no children, only one college major, no degree above a bachelor's degree and have a bachelor's degree from a Top 30 major. Wages are restricted to individuals who made between $7,000 and $400,000 annually as done in previous research.

Table 10c: Simulations of Hourly Gender Wage Gap ($'s)
Including Individuals with More Than Bachelor's Degree

	Actual	Equal Representation in Every Major	Equalize Traits	Equalize Traits and Major
Male Wage	25.28	23.87	25.28	23.87
Female Wage	21.89	23.21	22.41	23.77
Wage Gap	3.39	0.97	2.86	0.1
Wage Gap (%)	13.40%	2.76%	11.33%	0.41%
Reduction in Gap		**-80.53%**	**-15.43%**	**-97.12%**
Male Sample	38435	38435	38435	38435
Female Sample	42013	42013	42013	42013

*Notes: Data from ACS and O*NET. Actual is the unsimulated gender wage gap. Equal Representation in Every Major shows the gender wage gap when every major has a gender composition of 52% female and 48% male. Equalized Traits shows the gender wage gap if females have the same average occupational traits within college major as men. Equalize Traits and Major shows the gender wage gap when females have the same average occupational traits within college major as men and every major has a gender composition of 52% female and 48% male. The sample is restricted to individuals aged 24-29 who are employed full-time, full year who have no children, only one college major, not currently enrolled in school and have a bachelor's degree from a Top 30 major. Wages are restricted to individuals who made between $7,000 and $400,000 annually as done in previous research.

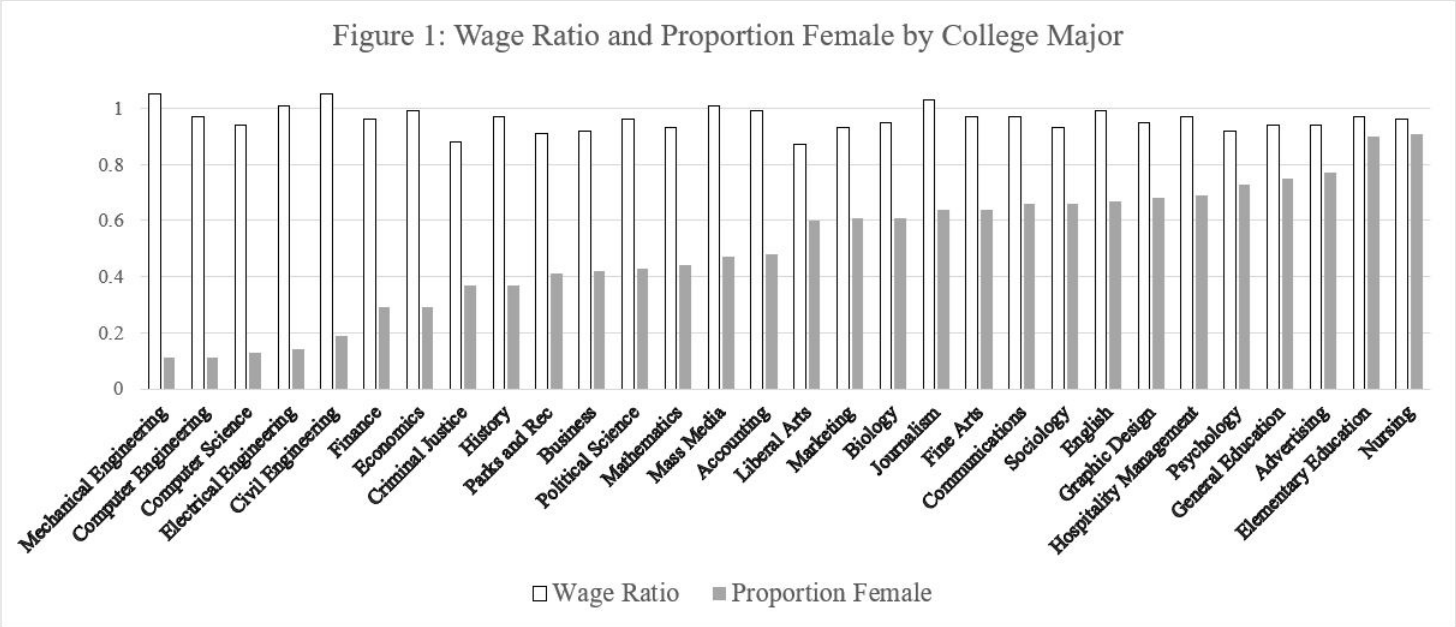
Table 11: Decompositions of Gender Wage Gaps Within College Major (Female Coefficients)

	Business	Psychology	Marketing	Computer Science	Communications	Criminal Justice
Wage Gap	1.77***	1.56***	1.63***	2.04***	0.56	2.50***
Explained	1.18***	1.16***	0.77***	0.77	0.68***	1.17***
Traits Sig	**1.15*** **	**0.88*** **	**0.52** **	**1.03*** **	**0.42* **	**1.01*** **
Other Demo	0.03	0.28**	0.25*	-0.26	0.26***	0.16*
Unexplained	0.59**	0.40	0.86**	1.27	-0.12	1.33***

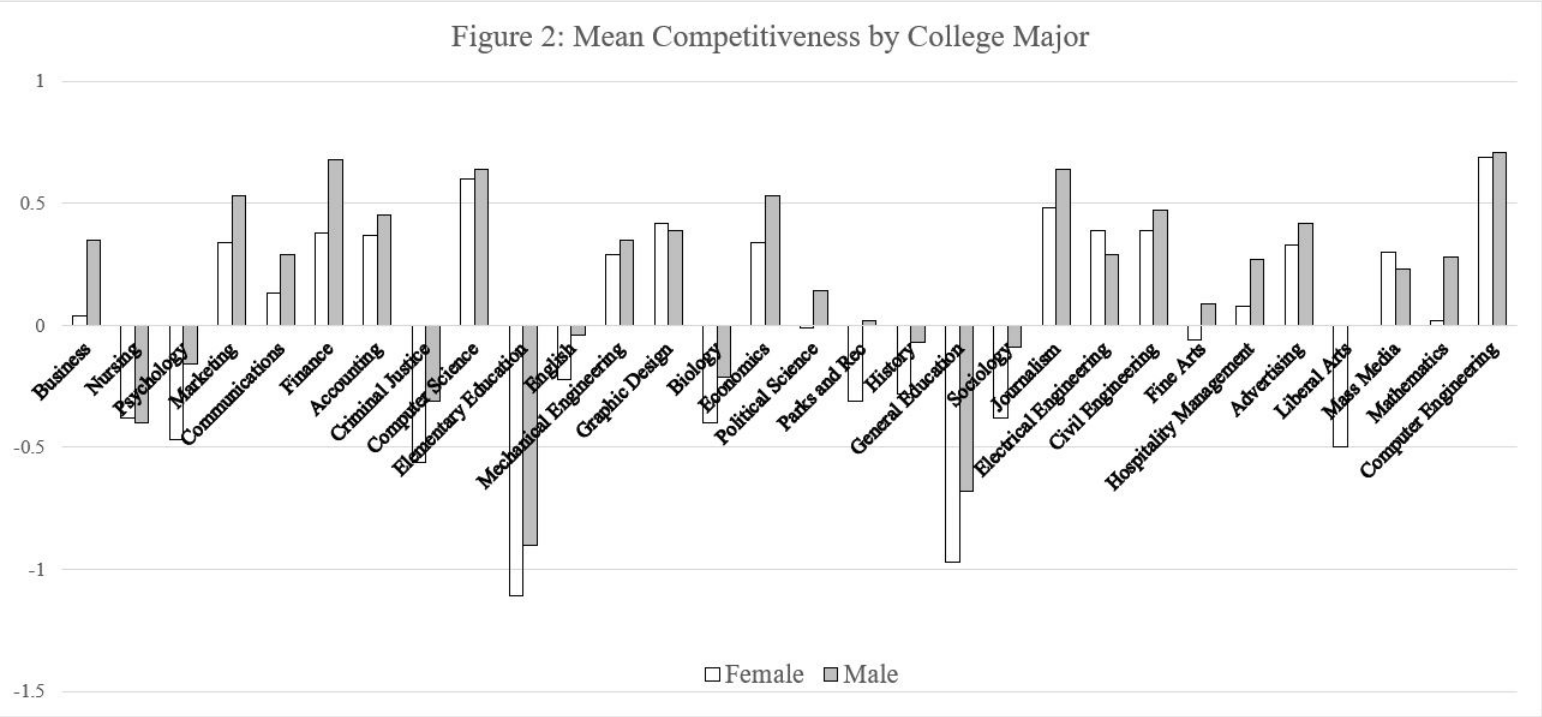
	English	Biology	Finance	Economics	Political Science	Parks and Rec
Wage Gap	0.10	0.97**	1.21**	0.30	0.93*	1.54***
Explained	0.62***	0.95***	0.97***	0.98***	0.73**	0.98***
Traits Sig	**0.46** **	**0.81*** **	**0.99*** **	**0.95*** **	**0.68*** **	**0.61*** **
Other Demo	0.16	0.14	-0.02	0.03	0.05	0.37***
Unexplained	-0.52**	0.02	0.24	-0.68	0.19	0.56

	History	Sociology	Fine arts	Hospital Management	Liberal Arts	Maths
Wage Gap	0.60	1.38*	1.07	0.50	2.41***	2.00**
Explained	0.98***	1.24***	1.21***	1.04***	1.26***	1.98***
Traits Sig	**0.86*** **	**1.22*** **	**0.94*** **	**0.64*** **	**1.31*** **	**1.96*** **
Other Demo	0.12	0.02	0.27*	0.40*	-0.05	0.02
Unexplained	-0.38	0.14	-0.14	-0.54	1.15	0.01

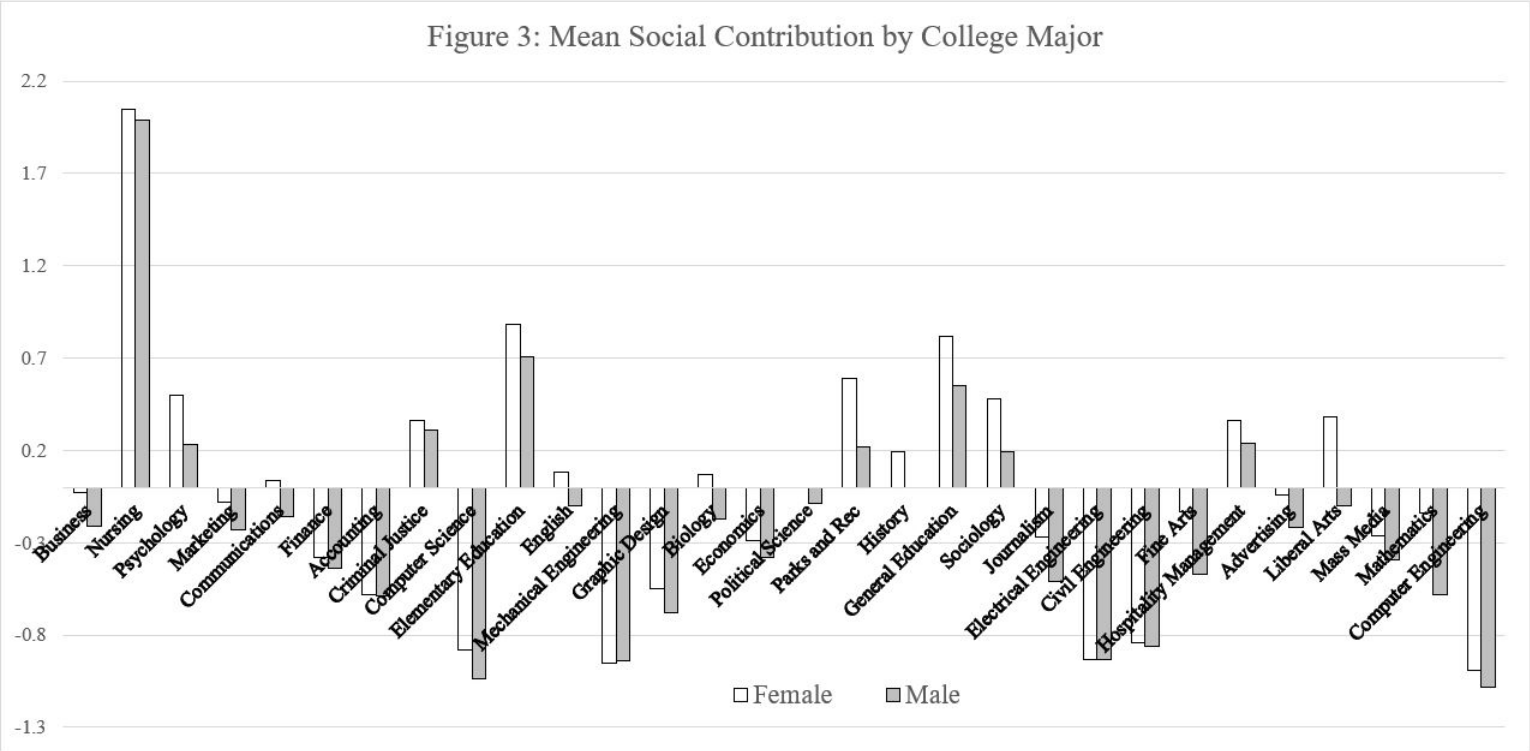
*Notes: Data from ACS and O*NET. Standard errors are clustered at the occupational level but not shown for brevity. *** p<0.01, ** p<0.05, * p<0.10. Female wage structure used as reference wage. This table shows O-B decompositions of within major hourly gender wage gaps. This table only shows the college majors where gender differences in occupational traits were a significant contributor to the gender wage gap. **Occ Traits** is the summed contribution of the individual occupational traits. **Other Demo** is the summed contribution of all demographic variables. The sample is restricted to individuals aged 24-29 who are employed full-time, full year who have no children, only one college major, no degree above a bachelor's degree and not currently enrolled in school. Wages are restricted to individuals who made between $7,000 and $400,000 annually as done in previous research.



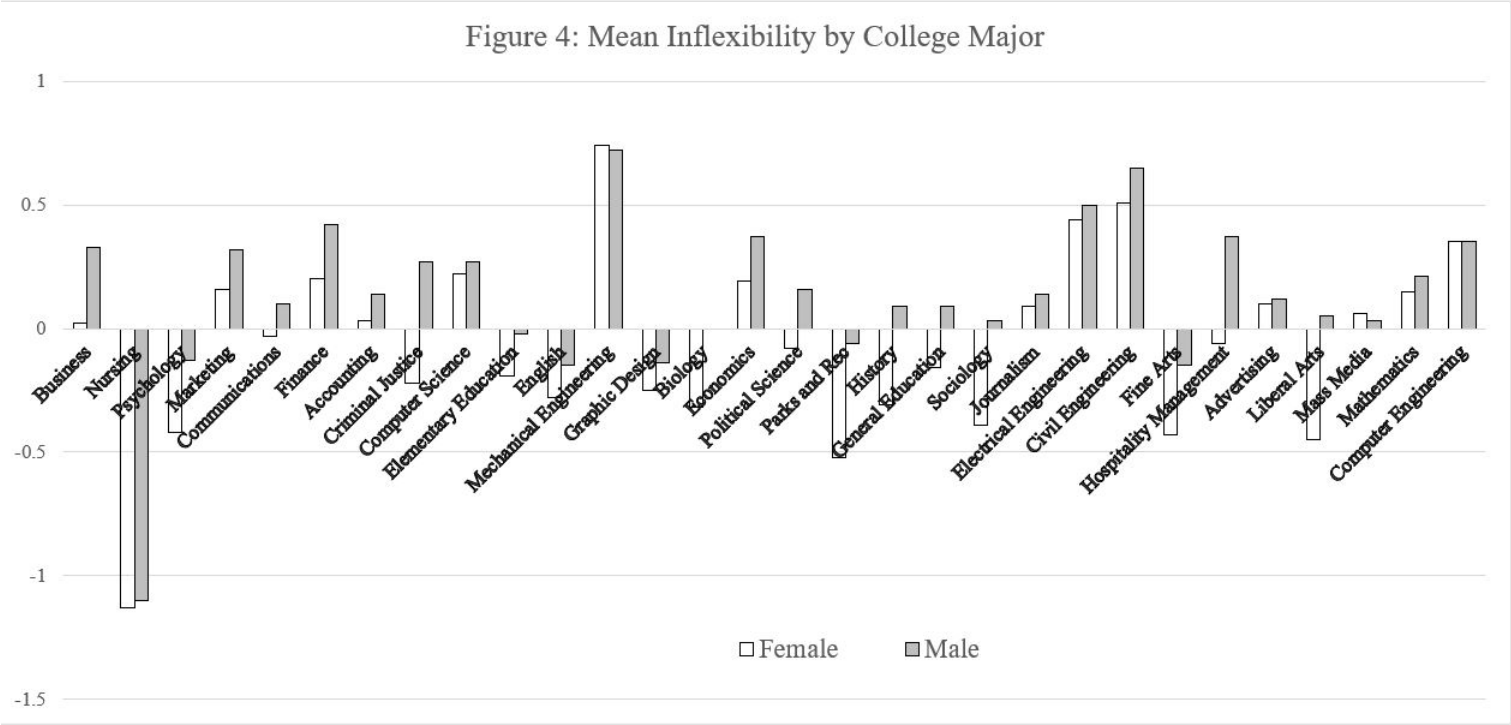
*Notes: Data from ACS. This figure shows the wage ratio (female wage / male wage from Table 2) and the proportion of graduates who are female for a given major. The sample is restricted to individuals aged 24-29 who are employed full-time, full year who have no children, only one college major, no degree above a bachelor's degree, not currently enrolled in school and have a bachelor's degree from a Top 30 major. Wages are restricted to individuals who made between $7,000 and $400,000 annually.



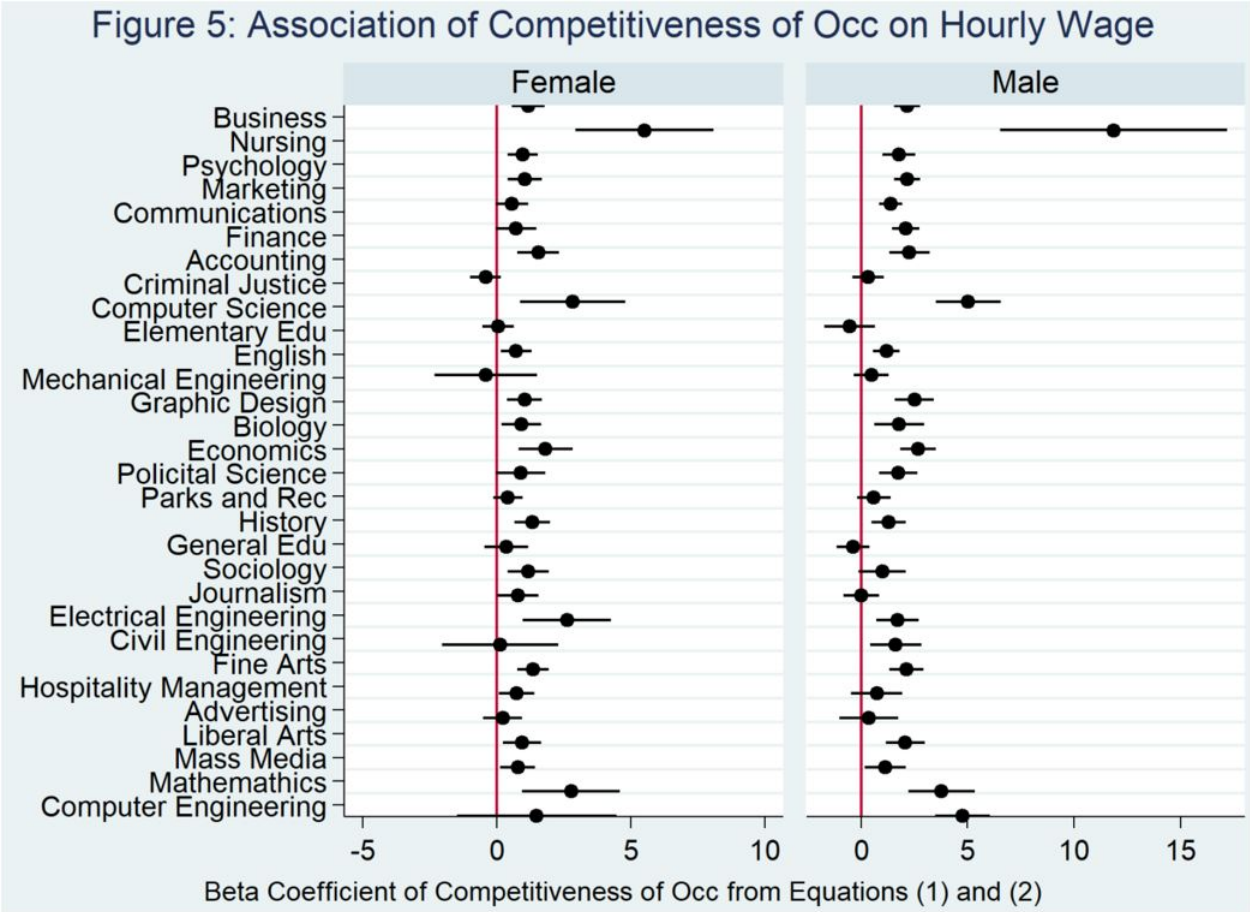
*Notes: Data from ACS and O*NET. This chart shows the results from Table 3 visually for mean competitiveness of major by gender. The sample is restricted to individuals aged 24-29 who are employed full-time, full year who have no children, only one college major, no degree above a bachelor's degree, not currently enrolled in school and have a bachelor's degree from a Top 30 major. Wages are restricted to individuals who made between $7,000 and $400,000 annually.



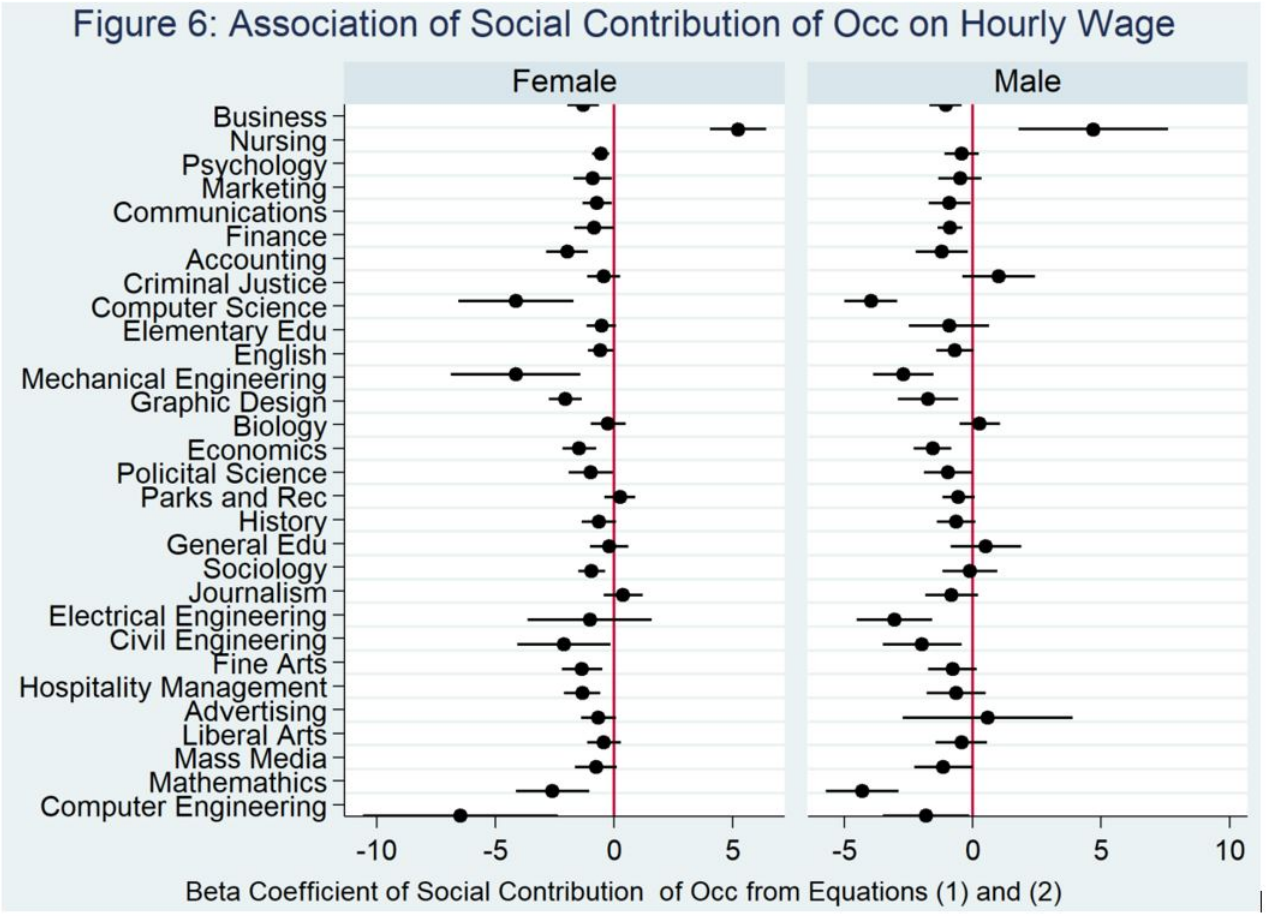
*Notes: Data from ACS and O*NET. This chart shows the results from Table 3 visually for mean social contribution of major by gender. The sample is restricted to individuals aged 24-29 who are employed full-time, full year who have no children, only one college major, no degree above a bachelor's degree, not currently enrolled in school and have a bachelor's degree from a Top 30 major. Wages are restricted to individuals who made between $7,000 and $400,000 annually.



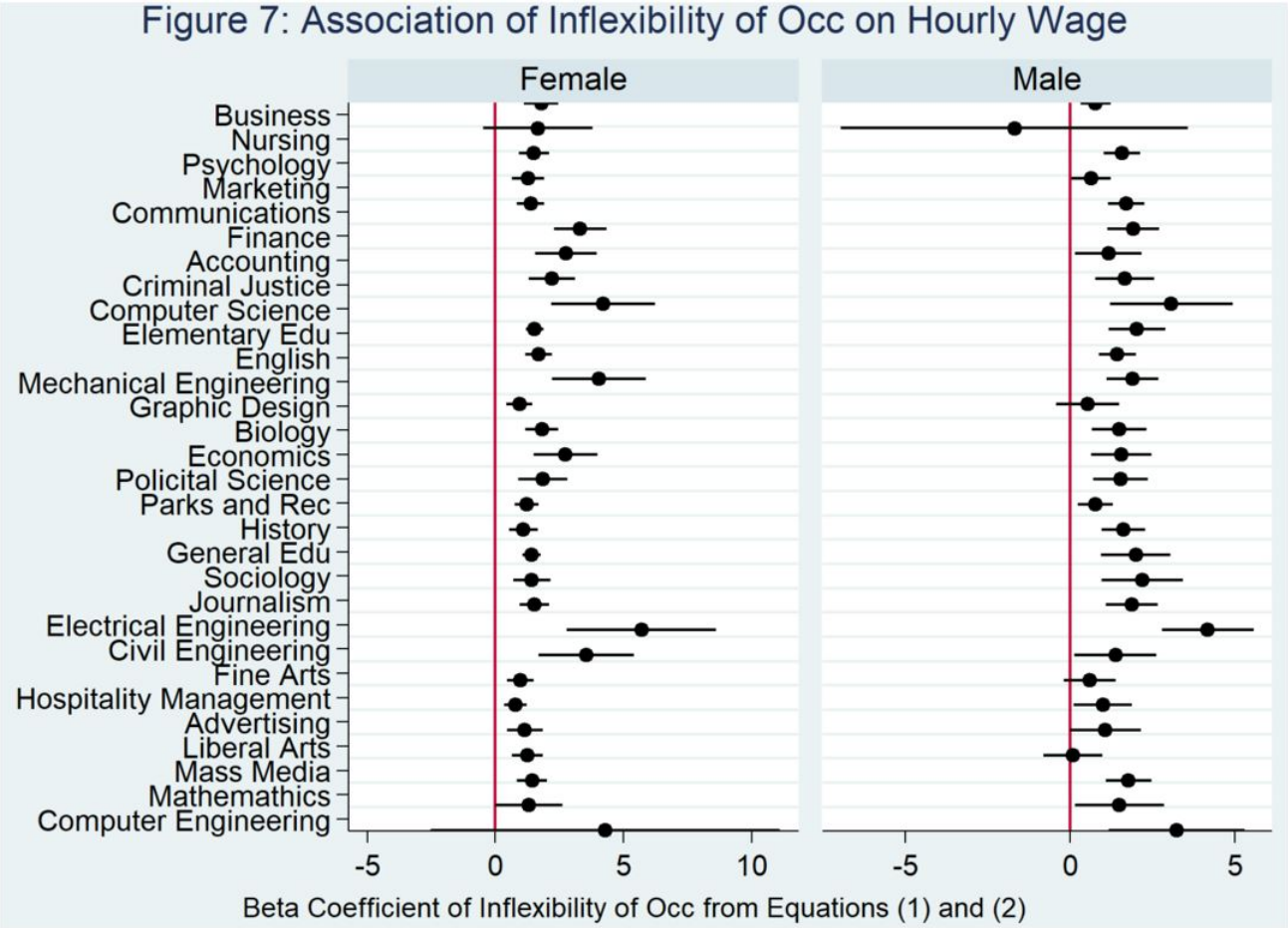
*Notes: Data from ACS and O*NET. This chart shows the results from Table 3 visually for mean inflexibility of major by gender. The sample is restricted to individuals aged 24-29 who are employed full-time, full year who have no children, only one college major, no degree above a bachelor's degree, not currently enrolled in school and have a bachelor's degree from a Top 30 major. Wages are restricted to individuals who made between $7,000 and $400,000 annually.



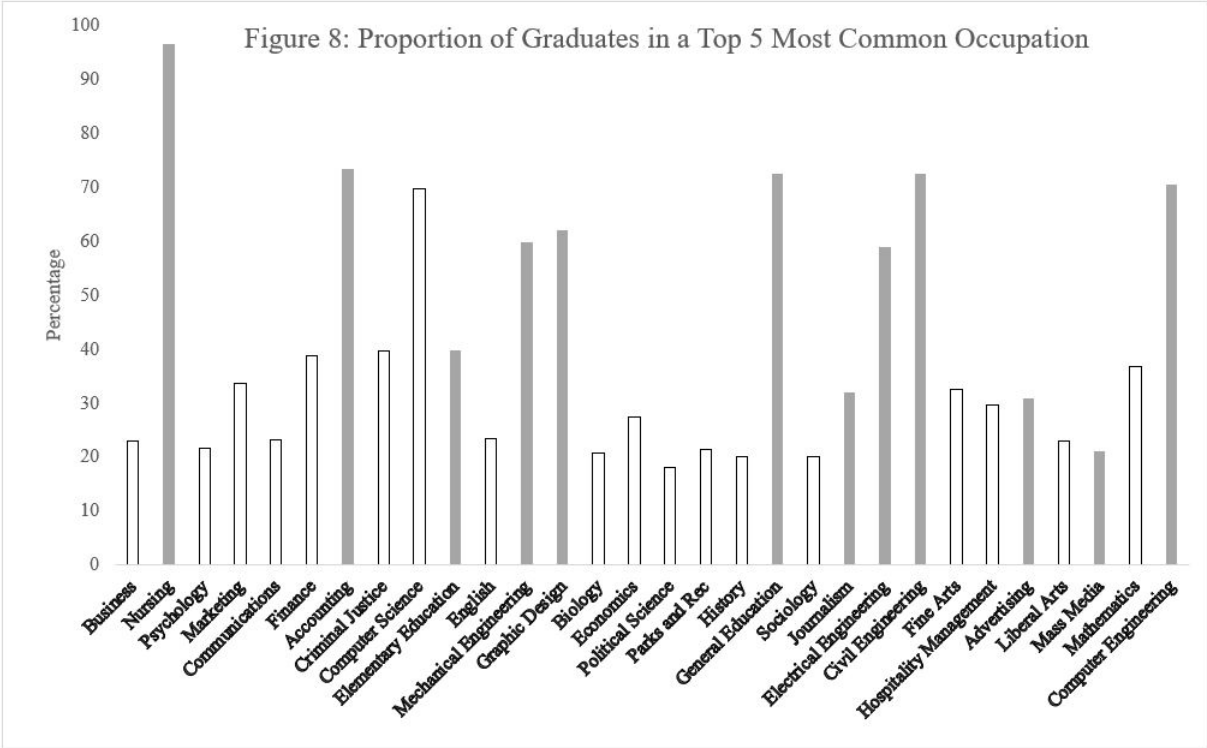
*Notes: Data from ACS and O*NET. This figure shows the beta coefficients from Equations (1) and (2) for the association of the competitiveness of an occupation on the hourly wage of the individual holding all other covariates constant. The coefficients are plotted to show if they are significantly different from 0 at the 10% significance level. Sample sizes are the same from Table 2. The sample is restricted to individuals aged 24-29 who are employed full-time, full year who have no children, only one college major, no degree above a bachelor's degree, not currently enrolled in school and have a bachelor's degree from a Top 30 major. Wages are restricted to individuals who made between $7,000 and $400,000 annually.



*Notes: Data from ACS and O*NET. This figure shows the beta coefficients from Equations (1) and (2) for the association of the social contribution of an occupation on the hourly wage of the individual holding all other covariates constant. The coefficients are plotted to show if they are significantly different from 0 at the 10% significance level. Sample sizes are the same from Table 2. The sample is restricted to individuals aged 24-29 who are employed full-time, full year who have no children, only one college major, no degree above a bachelor's degree, not currently enrolled in school and have a bachelor's degree from a Top 30 major. Wages are restricted to individuals who made between $7,000 and $400,000 annually.



*Notes: Data from ACS and O*NET. This figure shows the beta coefficients from Equations (1) and (2) for the association of the inflexibility of an occupation on the hourly wage of the individual holding all other covariates constant. The coefficients are plotted to show if they are significantly different from 0 at the 10% significance level. Sample sizes are the same from Table 2. The sample is restricted to individuals aged 24-29 who are employed full-time, full year who have no children, only one college major, no degree above a bachelor's degree, not currently enrolled in school and have a bachelor's degree from a Top 30 major. Wages are restricted to individuals who made between $7,000 and $400,000 annually.



*Notes: Data from ACS . This figure shows the proportion of graduates for a given major who are employed in one of the five most common occupations for graduates of that major. The grey bars indicate majors where gender differences in occupational traits in decompositions are not significantly associated with wages. White bars indicate majors from Table 6 where gender differences in occupational traits are significantly associated with wages. The sample is restricted to individuals aged 24-29 who are employed full-time, full year who have no children, only one college major, no degree above a bachelor's degree, not currently enrolled in school and have a bachelor's degree from a Top 30 major. Wages are restricted to individuals who made between $7,000 and $400,000 annually.

Appendix

6.1 Equalizing Occupational Traits and Weekly Hours for Annual Income Simulations

I do another simulation where in addition to equalizing occupational traits between men and women, I also equalize hours worked within major. To calculate what the average female income is when also equalizing hours worked per week I use equation (9). First, $\overline{\mathbf{X}}_c^f$ is a vector of average demographic variables within major for women which can be shown separating weekly hours from the other demographic variables:

$$\overline{\mathbf{X}}_c^f = \left[\overline{Hours}_c^f, \overline{\mathbf{Z}}_c^f\right] \tag{31}$$

$\hat{\beta}_{c,x}^f$ is a vector of the regression coefficients for the average demographic variables and can also be shown separating weekly hours from the other demographic variables:

$$\beta_{c,demo}^f{}' = \left[\beta_{c,hours}^f, \beta_{c,z}^f\right] \tag{32}$$

I can then re-write Equation (9) with the addition of women working the same weekly hours as men:

$$\ddot{Inc}_c^f = \beta_{0_c}^f + \overline{\mathbf{Occ}}_c^m \beta_{c,occ}^f + \overline{Hours}_c^m \beta_{c,hours}^f + \overline{\mathbf{Z}}_c^f \beta_{c,z}^f \tag{33}$$

Then the gender earnings gap can be calculated with the following equation:

$$\overline{Inc}^m - \ddot{Inc}^f = \sum_{c=1}^{30} \left(\frac{n_c^m}{N^m} \overline{Inc}_c^m\right) - \sum_{c=1}^{30} \left(\frac{n_c^f}{N^f} \ddot{Inc}_c^f\right) \tag{34}$$

6.2 Decompositions of Gender Wage Gaps Within College Majors

The Oaxaca-Blinder (O-B) decomposition is widely used in literature to analyse the gender wage gap as it enables one to dissect the gender wage gap into explained and unexplained components (Blinder, 1973; Oaxaca, 1973). The explained component describes how differences in characteristics of men and women contribute to the gender wage gap. The unexplained component describes if men and women receive different returns to their income for the same characteristics. To study if there is occupational segregation of recent college graduates, I use separate Oaxaca-Blinder decompositions for graduates of specific college majors

to see if gender differences in occupational traits significantly contribute to the gender wage gap of recent college graduates. The Oaxaca-Blinder decomposition estimates two separate linear regressions:

$$Wage_{ci}^{g} = \beta_{c,0}^{g} + \mathbf{Occ}_{ci}^{g}\beta_{c,occ}^{g} + \mathbf{X}_{ci}^{g}\beta_{c,x}^{g} + \epsilon_{ci}^{g} \tag{35}$$

where $Wage_{ci}^{g}$ is the annual income of individual i who is gender g, where $g = m$ for male and $g = f$ for female; c is college major from 1 to 30; $\beta_{c,0}^{g}$ is the intercept; $\mathbf{Occ}_{ci}^{g}$ is a vector of occupational traits; $\mathbf{X}_{ci}^{g}$ is a vector of demographic variables; $\beta_{c,occ}^{g}$ and $\beta_{c,x}^{g}$ are vectors of coefficients and ϵ_{ci}^{g} is the homoscedastic error term assumed to have a mean of zero. To analyse what gender differences affect the gender wage gap within each major, I first analyse the wages of men and women separately at their mean outcomes for each college major:

$$\overline{Wage}_{c}^{m} = \hat{\beta}_{c,0}^{m} + \overline{\mathbf{Occ}}_{c}^{m}\hat{\beta}_{c,occ}^{m} + \overline{\mathbf{X}}_{c}^{m}\hat{\beta}_{c,x}^{m} \tag{36}$$

$$\overline{Wage}_{c}^{f} = \hat{\beta}_{c,0}^{f} + \overline{\mathbf{Occ}}_{c}^{f}\hat{\beta}_{c,occ}^{f} + \overline{\mathbf{X}}_{c}^{f}\hat{\beta}_{x,c}^{f} \tag{37}$$

and then to analyse the mean gender wage gap, the difference is taken between the two linear regressions at the mean outcomes:

$$\overline{Wage}_{c}^{m} - \overline{Wage}_{c}^{f} = \left(\hat{\beta}_{c,0}^{m} - \hat{\beta}_{c,0}^{f}\right) + \overline{\mathbf{Occ}}_{c}^{m}\hat{\beta}_{c,occ}^{m} - \overline{\mathbf{Occ}}_{c}^{f}\hat{\beta}_{c,occ}^{f} + \overline{\mathbf{X}}_{c}^{m}\hat{\beta}_{c,x}^{m} - \overline{\mathbf{X}}_{c}^{f}\hat{\beta}_{c,x}^{f} \tag{38}$$

where $\overline{Wage}_{c}^{m} - \overline{Wage}_{c}^{f}$ describes the difference between the average wage of men and the average wage of women. $\overline{\mathbf{Occ}}_{c}^{m}$ is the vector of averages of the occupational traits for men and $\overline{\mathbf{Occ}}_{c}^{f}$ is the vector of averages of the occupational traits for women; $\overline{\mathbf{X}}_{c}^{m}$ is the vector of averages of the demographics for men and $\overline{\mathbf{X}}_{c}^{f}$ is the vector of averages of the demographics for women; $\hat{\beta}_{c,occ}$ are vectors of estimated coefficients for men and women for occupational traits; $\hat{\beta}_{c,x}$ are vectors of estimated coefficients for men and women for demographics . $(\hat{\beta}_{c,0}^{m} - \hat{\beta}_{c,0}^{f})$ is the difference in intercepts between male and female respondents. This intercept includes omitted variables that may be potentially important for estimation.

By adding and subtracting counterfactual means, $\overline{\mathbf{Occ}}_{c}^{f}\hat{\beta}_{c,occ}^{m}$ and $\overline{\mathbf{X}}_{c}^{f}\hat{\beta}_{c,demo}^{m}$, this equation can be rewritten in the standard Oaxaca-Blinder Decomposition notation:

$$\begin{aligned}\overline{Wage}_{c}^{m} - \overline{Wage}_{c}^{f} = & \\ & \left(\hat{\beta}_{c,0}^{m} - \hat{\beta}_{c,0}^{f}\right) + \overline{\mathbf{Occ}}_{c}^{m}\hat{\beta}_{c,occ}^{m} - \overline{\mathbf{Occ}}_{c}^{f}\hat{\beta}_{c,occ}^{f} + \overline{\mathbf{X}}_{c}^{m}\hat{\beta}_{c,x}^{m} - \overline{\mathbf{X}}_{c}^{f}\hat{\beta}_{c,x}^{f} \\ & + \overline{\mathbf{Occ}}_{c}^{f}\hat{\beta}_{c,occ}^{m} - \overline{\mathbf{Occ}}_{c}^{f}\hat{\beta}_{c,occ}^{m} + \overline{\mathbf{X}}_{c}^{f}\hat{\beta}_{c,x}^{m} - \overline{\mathbf{X}}_{c}^{f}\hat{\beta}_{c,x}^{m}\end{aligned} \tag{39}$$

$$\overline{Wage}_c^m - \overline{Wage}_c^f =$$
$$\left(\hat{\beta}_{c,0}^m - \hat{\beta}_{c,0}^f\right) + \left(\overline{\mathbf{Occ}}_c^m - \overline{\mathbf{Occ}}_c^f\right)\hat{\beta}_{c,occ}^m + \overline{\mathbf{Occ}}_c^f\left(\hat{\beta}_{c,occ}^m - \hat{\beta}_{c,occ}^f\right)$$
$$\left(\overline{\mathbf{X}}_c^m - \overline{\mathbf{X}}_c^f\right)\hat{\beta}_{c,x}^m + \overline{\mathbf{X}}_c^f\left(\hat{\beta}_{c,x}^m - \hat{\beta}_{c,x}^f\right) \quad (40)$$

With this decomposition one can use males or females as the reference wage. $(\overline{\mathbf{Occ}}_c^m - \overline{\mathbf{Occ}}_c^f)\hat{\beta}_{c,occ}^m$ shows how much of the gender wage gap is explained by differences in occupational traits between men and women if women were paid the same as men. $\overline{\mathbf{Occ}}_c^f(\hat{\beta}_{c,occ}^m - \hat{\beta}_{c,occ}^f)$ shows how much of the gender wage gap is unexplained due to men and women being compensated differently for the same occupational traits. Furthermore, $(\overline{\mathbf{X}}_c^m - \overline{\mathbf{X}}_c^f)\hat{\beta}_{c,x}^m$ shows how much of the gender wage gap is explained by differences in demographics between men and women if women were paid the same as men. $\overline{\mathbf{X}}_c^f(\hat{\beta}_{c,x}^m - \hat{\beta}_{c,x}^f)$ shows how much of the gender wage gap is unexplained due to men and women being compensated differently for the same demographics. Using this decomposition method, it is simple to calculate the detailed decomposition of the explained portion of the gender wage gap due to gender differences in occupational traits:

$$\left(\overline{\mathbf{Occ}}_c^m - \overline{\mathbf{Occ}}_c^f\right)\hat{\beta}_{c,occ}^m = \sum_k \left(\overline{Occ}_{ck}^m - \overline{Occ}_{ck}^f\right)\beta_{ck,occ}^m \quad (41)$$

where k is each explanatory variable; $\overline{Occ}_{ck}^m$ is the sample average for the given occupational trait for men and $\overline{Occ}_{ck}^f$ is the sample average for the given occupational trait for women; $\hat{\beta}_{ck,occ}^m$ is the coefficient for occupational trait k for men. This detailed decomposition is one of the reasons why the Oaxaca-Blinder decomposition method is so widely used because it enables one to calculate how much each explanatory variable contributes to the gender wage gap. This is how I show whether gender differences in occupational traits significantly contribute to the gender wage gap for specific college majors.