Undergraduate Education and the Gender Wage Gap: An Analysis of the Effects of College Experience and Gender on Income

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Abstract

Labor and education economists have long been interested in the link between undergraduate education and earnings. In addition, studies have addressed the connections between gender and college major and GPA, as well as between gender and income. This paper brings all of these together in order to show that college major choice does have a significant effect on earnings, and that this effect differs with gender and across majors. The results show that controlling for college major, ability measures, graduation year, and GPA can help to explain a majority of the gender pay gap. Finally, the thesis then utilizes the Oaxaca-Blinder Decomposition to break down the price and composition effect of undergraduate education on the gender pay gap.

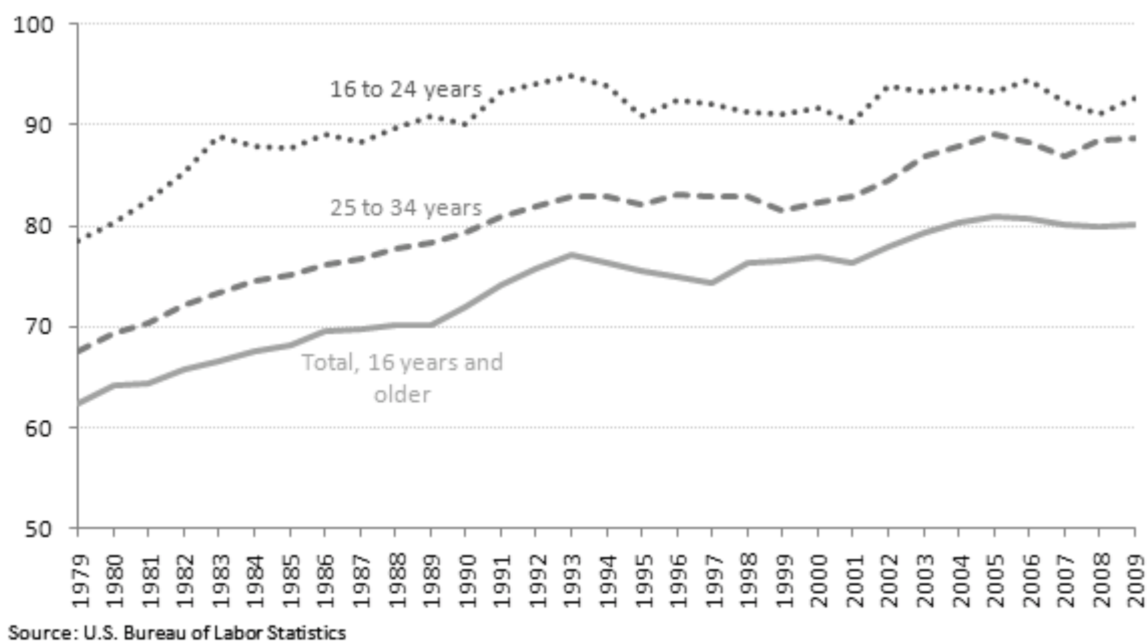
JEL Classification: A22, J16

Keywords: College, Gender, Income

I. Introduction

In the 1970s, women earned only 60 cents for every dollar that men earned (Blau and Kahn, 2007). Yet, from the years 1980 to 2000, the gender earnings gap narrowed significantly. For all full-time workers during this period, the gap narrowed by 28 percent. For young females in higher-skilled jobs, specifically those younger than 50 years old, the gap narrowed by 38 percent (Blau and Kahn, 2000). Despite these facts, according to Blau and Kahn (2000), in 1999 the weekly earnings of female full-time workers were only 76.5 percent of male earnings. Although this is a great increase from thirty years ago, a large gap still exists. Thus, progress has been made in closing the gender pay gap, but a recent plateau in this progress raises concern.

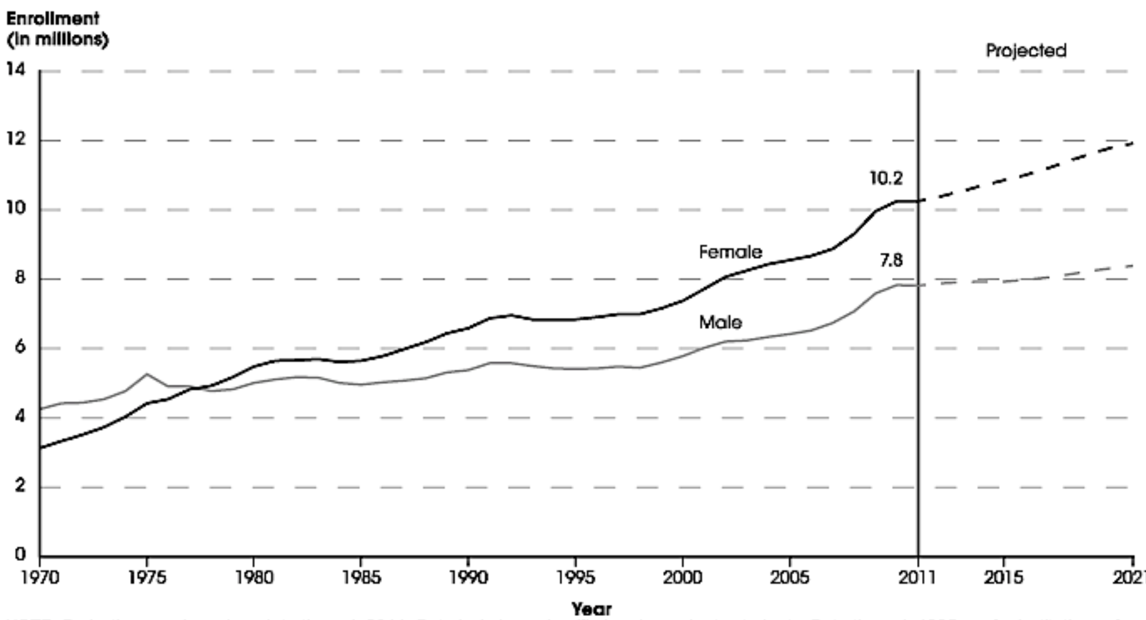
Figure 1: Women's Earnings as a Percent of Men's, Median Usual Weekly Earnings of Full-Time Wage and Salary Workers, by Age, 1979-2009



As Figure 1 shows, the female-male earnings ratio has increased significantly since 1979, but plateaued in the mid-90's and has remained relatively steady since. By identifying its causes can we identify ways to close the gender pay gap fully?

The narrowing of the gender pay gap is undeniably linked to the increase in female participation in higher education, which has been a trend since the 1980s as well. In 1960, women were less than 40 percent of college undergraduates. Currently, the majority of college students are females (Goldin et al., 2006).

Figure 2: Actual and Projected Enrollment in Degree-Granting Postsecondary Institutions, by Sex: Fall 1970-2021



NOTE: Projections are based on data through 2011. Data include unclassified undergraduate students. Data through 1995 are for institutions of higher education, while later data are for degree-granting institutions. Degree-granting institutions grant associate's or higher degrees and participate in Title IV federal financial aid programs. The degree-granting classification is very similar to the earlier higher education classification, but it includes more 2-year colleges and excludes a few higher education institutions that did not grant degrees. Some data have been revised from previously published figures.
SOURCE: U.S. Department of Education, National Center for Education Statistics, Higher Education General Information Survey (HEGIS), "Fall Enrollment in Colleges and Universities" surveys, 1970 through 1985; Integrated Postsecondary Education Data System (IPEDS), "Fall Enrollment Survey" (IPEDS-EF:86-99); and IPEDS Spring 2001 through Spring 2012, Enrollment component. See *Digest of Education Statistics 2012*, tables 2 and 240 and *Digest of Education Statistics 2011*, table 214.

Figure 2 shows the increase in female participation in postsecondary education, with females becoming the majority of college students between 1975 and 1980. The figure also shows that the reversal of the college gender gap is expected to continue to increase in magnitude through 2021, based on projections of the population of college-aged males and females, income less taxes, and unemployment rates (U.S. Department of Education, 2012). In addition, the wage premium for a bachelor's degree has risen significantly since

1980, especially for women (Francis, 2007). Increases in undergraduate enrollment and changes in college major choice for females have put them on the track to close the gender gap.

In a 2009 American Community Survey conducted by the Census Bureau, economists found that math training is related to higher wages (Izzo, 2012). However, it is widely acknowledged that a majority of women choose humanities majors over those in math and science. Yet, that majority has been growing smaller since the 1980s. In fact, females made up about 45 percent of the undergraduate business degrees in 1984-5 and 50 percent by 2001-2, a sharp rise from only 9.1 percent in 1970-1. In addition, since 1970 there have also been increases in the female percentage of bachelor's degrees in the life sciences, physical sciences, and engineering disciplines (Francis, 2007). Other than undergraduate major, another factor that may have a connection to higher earnings is one's college GPA, and women have made major strides in that area as well.

In fact, women at undergraduate institutions now outperform men in the classroom. Studies in Florida and Texas have found that men enroll in fewer credits and receive lower grades than women during their first semester of college. This persists until graduation, with male students earning fewer degrees and graduating with lower GPAs (Conger and Long, 2010). Conger and Long (2010) found that, for example, across 11 public universities in Florida, males graduated with an average of 6.6 fewer credits than females. In addition, the men had an average GPA 0.2 points lower than the female average. Both of these results were statistically significant (Conger and Long, 2010).

Despite all of the strides women have made since the 1950's, especially in the area of higher education, the gender gap still continues to exist. According to data from the 1985 Survey of Recent College Graduates, among all those surveyed with a Bachelor's Degree, the female contingent earned 18 percent less than the males (Weinberger, 1998). Thus, in this paper, I delve into the connection between college experience and wages further by investigating specific features of the undergraduate academic experience, including major selection and GPA, and the effect they have on female earnings. Yes, the wage gap has narrowed, but are females with strong grades at a better advantage? Or does a woman have to pursue traditionally "male-dominated" areas of study to bridge the wage gap? I explore if the rise of females in business, science, and math fields is directly linked to an increase in wages for females in their post-graduate careers. Do females in math, science and engineering majors benefit just as much as males from choosing a more traditionally rigorous area of study? I investigate whether the higher performance of women in college actually correlates to an increase in earnings post graduation, especially in comparison to their male peers who have followed a similar academic track. I compare the analyses of the earnings in the last year, job type, college major, and grade point average of the men and women to each other, in order to determine whether or not a similar academic experience translates into comparable compensation after graduation. In addition, I compare the females against each other, in order to reveal whether it is enrollment in what is perceived to be a "difficult" major or a better academic performance that really makes a difference in future compensation for women. Finally, I break down the gender pay gap into price and composition effects based on the theory of the Oaxaca-Blinder Decomposition and various undergraduate education indicators. The main goal of this investigation is to draw conclusions regarding whether a female's choice of major, in addition to strong performance in the classroom, really does pay off, literally, as much as it does for their male peers.

The paper is organized as follows. Section II reviews the existing literature related to the link between undergraduate education and the gender pay gap, as well as the economic theory on the Oaxaca-Blinder Decomposition. Section III describes the National Longitudinal Survey of Youth, 1997, the dataset used for this analysis. Sections IV and V present the empirical results, which show the great significance of college major on the decomposition of the gender pay gap. More specifically, the sections illustrate that controlling for college major, graduation year, ability, GPA, job industry, and other demographic indicators can explain a majority of the gender pay gap. Section VI contains the conclusions I have drawn from these results.

II. Literature Review and Decomposition Framework

The issue of wage differentials in the United States is one that has been studied widely in economics, whether it be differences based on gender, race, or other factors. Many researchers have found that by breaking down wage differentials among different groups using various methodologies, some differences in wages can be explained, while portions of the differences still remain enigmatic. Huffman and Cohen (2004) found that, even when employed in like occupations, African American workers in the United States are paid less than similar white workers. Johnson and Lambrinos (1985) concluded that there are significant wage differentials between American handicapped workers and non-handicapped workers, and that these differences are even more pronounced between males and females. More specifically related to my paper, Blau and Kahn (2004) investigated the relation between the convergence of the gender pay gap in the 1980's and the plateau of the 1990s. They found that there was a "greater negative effect of glass ceiling barriers on women's relative wages in the 1990s," which could possibly reflect discrimination (Blau and Kahn, 2004). It has been established in economic literature that wage differences between men and women in the United States exist. This paper will show whether or not wage differentials between men and women in the same industry are still significant when broken down by college major and GPA.

Many existing works of economic literature have examined issues related to female undergraduate choices and employment after graduation, but have not explored exactly the same themes as my analysis. Goldin, Katz, and Kuziemko (2006) investigate trends in female enrollment in undergraduate education with data sets from 1957, 1972, and 1992. They emphasize factors in these changes that differed by gender or were varied in their consequences. One of these factors is "expectation of future labor force participation" (Goldin et al., 2006). The authors examine results of the National Longitudinal Survey of Young Women to address this factor. The survey asked women to identify whether they expected to be "at work" or "at home, with a family" at age thirty-five (Goldin et al., 2006). In 1968, between thirty and thirty-five percent chose "at work," but by 1979 the number had risen to eighty percent. Delving into this further, the survey also showed that there existed a fourteen percent difference in college attendance and completion rates between women who, while in high school, stated they expected to be in the labor force at age thirty-five and those who did not (Goldin et al., 2006). This reveals that the reversal of the gap does have to do with female expectations about working after graduation, and isn't solely related to changes in social norms or the desire to continue one's studies. I do not explore the work expectations of females who have attended college, but rather the reality of female career choices, including their preparation for these careers while pursuing their undergraduate degrees. Like Goldin et al., I also use the National Longitudinal Survey data in my research, and thus, for females, I expect to see a strong link between undergraduate academic choices and performance and employment after college in my results. The results are consistent with this view.

Another paper that explores aspects of female undergraduate education is "Determinants of College Major Choice: Identification Using an Information Experiment" by Matthew Wiswall and Basit Zafar of the Federal Reserve Bank of New York (2011). This paper includes an investigation into gender differences in major choice. Specifically, the authors examine the differences between male and female students' perception of average earnings within different fields. Wiswall and Zafar found that beliefs about future relative major choices are positively and strongly associated with beliefs about future self-earnings. However, this factor was a substantially smaller determinant in women than in men. The authors found that, to women, ability in the field was a much more important factor in choosing their major. This raises the question of whether the women who choose math, science and other business-related majors have higher abilities in these fields than their male counterparts. In addition, the paper examined the difference between male and female perception of earnings after majoring in different fields. An interesting result was that both males and females overestimated female full-time earnings after majoring in Economics and business fields by about thirty percent (Wiswall and Zafar, 2011). This finding suggests that perhaps women in these fields do not earn as much as their male peers. I will not be investigating the reasons why women and men choose different majors or their perceptions of future earnings; instead, I will show the connection between their major choices and actual earnings. My research will determine whether Wiswall and Zafar's findings about female earnings are true across datasets, or whether females who major in Economics and business fields choose jobs in different industries than males, thus explaining the difference between perceptions of earnings and reality. My thesis will also show if the difference has any link to academic performance while in college.

Zafar (2013) also investigated the factors which lead males and females to choose their college majors in even more depth. Results of a study of sophomores at Northwestern University showed that the most important determinants of major choice were enjoying classwork, enjoying work at future jobs, and parental approval. A very interesting result of Zafar's study is that non-monetary reasons account for 75 percent of choice behavior for females, but only account for 45 percent of choice behavior for males. These preferences extend into the workplace (Zafar, 2013). My dataset will not be limited to graduates of prestigious colleges such as Northwestern University, but I will be able to observe differences in major choice between females and males who have demonstrated similar abilities in standardized tests. In addition, Zafar's research makes it apparent that accounting for job industry selection will be important to my investigation of the link between college academic experience and earnings.

The paper "Why are Men Falling Behind? Gender Gaps in College Performance and Persistence," mentioned during the Introduction, by Dylan Conger and Mark C. Long (2010) is also useful to examine. The authors study the disparity between male and female college performance. They find that women on average earn more credits, higher grades, and are more likely to graduate. However, the investigation also reveals that much of this difference can be explained by chosen area of study; females tend to choose “easier” majors than males (Conger and Long, 2010). Thus, the paper suggests that college major choice is a more important determinant of future earnings than GPA. Like Conger and Long, I will be comparing the GPAs of males and females, however, I focus on math, science, and business fields, and link the GPAs to future earnings. By examining both the subject’s major choice and GPA’s effect on earnings, my research will reveal whether the females who do not choose “easy” humanities tracks do make as much as men with similar educational backgrounds.

Hamermesh and Donald (2004) also address the link between college experience and income. Their paper provides a detailed examination of undergraduate major, course selection, grades in these courses, and subsequent earnings twenty years post-graduation. Hamermesh and Donald found that the highest-earning majors (Honors and “hard” business majors) averaged almost three times that of the lowest (Education), and that the fraction of women in the highest-earning majors was lower than in the lowest-earning majors. Another interesting result of the study was that the adjusted female wage gap for single women compared to single men is only eight percent, while the adjusted gap between married women and married men is twenty-five percent. The authors also noted that within a major (results for both males and females combined), going from a B to A average GPA raised annual earnings by about seven percent (Donald and Hamermesh, 2004). My research will be similar in investigating the effects of major choice and GPA on earnings, however, I am more specifically looking at the differences in these effects between males and females. It is important to use my research to extend the results of this study further to note whether the highest-earning females pursued more difficult areas of study and/or earned higher grades.

Another source that is relevant to my investigation is the paper "Gender Differences in Executive Compensation and Job Mobility" by George-Levi Gayle, Limor Golan, and Robert A. Miller. This paper is especially interesting because it focuses on women who have reached executive level positions. The authors examine compensation data with background characteristics, including education. The results showed that, conditional on survival as an executive, women have a higher probability of becoming CEO. However, average career compensation was lower for female executives than for male executives (Gayle et al., 2012). My research shows whether or not females who have chosen a rigorous area of study and remain in the work force as long as their male counterparts receive the same return in in income.

In 2010, Lin published the paper "Gender Wage Gaps by College Major in Taiwan: Empirical Evidence from the 1997-2003 Manpower Utilization Survey." This paper contains a very similar purpose to my investigation, but uses data from Taiwan rather than the United States. When observing overall gender gaps by college major, the results showed that Agriculture, Literature, and other similar majors had smaller gender pay gaps, while Medicine and Business showed the largest gaps. In addition, the gender pay gaps were statistically significant in the majors of Education, Engineering, Law, Business, and Medicine. However, Lin found that controlling for college major with dummy variables increases the proportion of the price effect (also known as the characteristic effect) in the Oaxaca-Blinder Decomposition, meaning that individual characteristics became more important to wages than whether the individual was a male or female. He also discovered that when investigating the gender pay gap by occupation industry, wage differences were "statistically negligible" in all majors except for medicine (Lin, 2010). Still, some differences did exist between male and female pay after majoring in certain fields. Education, Law, Business, and Engineering demonstrated a gender pay gap that slightly favored males, while Literature, Education, and, surprisingly, Science majors demonstrated a pay gap that actually favored females. Thus, it will be important in my research to also break down the gender pay gap by job industry and type, as well as major. I use the methodology of this paper, which applied a pooled Neumark estimator to the Oaxaca-Blinder Decomposition, to help guide me through my research. However, Lin's paper focuses on the gender gap within a major, while mine also addresses the gap across majors.

Previous economists, including Lin, have studied the effects of multiple variables on wages by applying the Neumark estimator to implement the Oaxaca-Blinder Decomposition. The Oaxaca-Blinder Decomposition attempts to decompose outcomes (in this case, earnings) into price and decomposition effects. Using this theory, one is able to break down the "price effect" and the "composition effect" on average wages. The Neumark estimator was introduced by David Neumark (1988) as a method to build a wage structure that is nondiscriminatory, but that is based on the discriminatory tastes of employers. Neumark assumed that the utility function for discriminatory tastes of employers within a certain type of labor (skilled, unskilled) is homogenous of degree zero with respect to labor inputs from each of the genders. With this assumption in mind, he found that the nondiscriminatory wage structure is the coefficient vector of the wage regression equation over the pooled sample, and, thus, can be represented as a weighted average. Hence, weighted-average earnings can be used to derive the Oaxaca-Blinder Decomposition (Neumark, 1988). The average wage for a gender is the weighted average of the wages the gender earns in each occupation. The weights are the share of workers of a given gender within each occupation. Roughly speaking, in a general application of the Oaxaca-Blinder Decomposition, the price effect has to do with wage differentials across genders for certain occupations, and the composition effect is related to differences in occupational choice between males and females. In my paper, I separate the differences in mean wages between males and females into those attributed to individual characteristics (the "price effect") and the component associated with the differences in the characteristics themselves (the "composition effect"). To be more specific, the price effect I am investigating is: given a specific major or GPA, what are the differences in wages between males and females. The composition effect would be something along the lines of: females in general tend to have lower wages because they tend to choose humanities majors over math, science, and business fields. My results quantify both the composition and price effect.

Utilizing the background information found in the aforementioned sources, plus the results of further research, I investigate the undergraduate college experience for women and its connections to the narrowing of the gender pay gap. Unlike much of the current literature, I do not focus on solely female choices and results in undergraduate academics, but instead connecting these to their lives after graduation. Similar research on the link between academic decisions while in college and earnings has been done, but it does not specifically address this link's effect on the gender pay gap, or the research does not use data from the United States. I do not examine how the gap has changed over time, rather, I paint a picture of the gap relative to the college experience as it exists today.

III. Data

The dataset I have chosen to accomplish my goals part of a broad U.S. government initiative known as the National Longitudinal Surveys. The National Longitudinal Surveys are a set of surveys conducted by the Bureau of Labor Statistics. These surveys have gathered data on the labor market activities and special life events (marriage, childbirth, etc.) of multiple groups of men and women in the United States. The surveys have been conducted for over four decades, beginning with the National Longitudinal Surveys of Young Men and Older Men in 1966 (Bureau of Labor Statistics, 2011). The survey that I use in my research is the National Longitudinal Survey of Youth 1997.

The National Longitudinal Survey of Youth 1997, or NLSY97, surveyed a nationally representative sample of approximately 9,000 people in the United States who were between the ages of 12 and 16 on December 31, 1996. The first round of the survey was conducted in 1997, in which the young people and their parents participated in hour-long individual interviews. This round also included a questionnaire revealing each youth's demographic information as well as family background and history. The youths continue to be interviewed annually about educational and labor market experience, as well as other personal relationship and life events (Bureau of Labor Statistics, 2011). The NLSY97 data contains numerous variables which are essential to my research.

The NLSY97 measured detailed information on both the subjects' educational and employment experience. Employment data includes occupation, industry, hours, overtime hours, previous year's income from wages or salary, benefits available at employer, and general job satisfaction. Some of the educational variables measured are type of college attended (2-year, 4-year, public, or private), cost of attendance at the college, type and amount of educational loans and financial aid, type of degree received, field of study in each term, and grade point average in each term. Other variables that could be interesting to observe are current marital status, number, sex, and ages of children, and fertility expectations. And, of course, all surveyed do have to disclose their gender (Bureau of Labor Statistics, 2011). Thus, the NLSY97 does include all the variables that I need to conduct my research. However, the dataset does not specify exactly which undergraduate institution the subjects attended, thus, I was unable to control for the academic rigor of the college. Yet, the dataset does contain some proxies for ability measures, such as Armed Forces Qualification Test results. All in all, the NLSY97 is a very detailed dataset and is more than sufficient to complete my investigation.

The entire NLSY97 dataset sample is made up of 8,984 individuals. 4,385 of these subjects are female (48.81 percent of the sample) and 4,599 are male (51.19 percent). The sample I will be using contains solely the subjects who have received Bachelor's Degrees. The NLSY97 survey asks the subjects each year if they have received a degree or diploma since the last date they were interviewed. Thus, one must find how many subjects indicate they have received a Bachelor's degree in each of the survey years, and add them together. I have shown the results here, broken down by sex

Table 1: Subjects with a Bachelor's Degree, by Sex

Gender	Subjects
Male	668
Female	918
TOTAL	**1586**

The overall sample size of individuals with a Bachelor's Degree is 1586 subjects. It is interesting that one can already see that more females than males have indicated that they have received a Bachelor's degree. In my sample, about 58 percent of those with a Bachelor's Degree are female. According to the U. S. Department of Education (2012), in 2009-10, females earned approximately 57 percent of Bachelor's Degrees. Thus, my sample is consistent with national trends. Yet, looking at the specific Stata results, the data does show that many subjects stopped being interviewed during each round, especially during the later years. Thus, there may be some sample selection bias here.

Next, the sample was broken down further by college major. The NLSY97 asks subjects enrolled in college whether they are majoring in 1 of 37 different areas. Those which I include in my investigation as business, science, or math fields are: Biological Sciences, Business Management, Computer/Information Science, Economics, Engineering, Mathematics, and Physical Sciences. The NLSY97 data does not have a specific indicator for the major that the subjects receive their Bachelor's Degree in. Rather, each year, the survey asks each subject to indicate their major during each term since they were last interviewed. Thus, I created my own variable by specifying each individual's major indicator in the year in which they received their Bachelor's Degree, matching using the subject's identification number. The results are shown in the following table, separated by sex.

Table 2: College Major upon Graduation, by Sex

Major	Males	Females	Percent of STEMB Total
Biological Sciences	27	44	11.04
Business Management	165	171	52.26
Computer Science	55	12	10.42
Economics	36	16	8.09
Engineering	59	21	12.44
Mathematics	12	8	3.11
Physical Sciences	8	9	2.64
TOTAL	**362**	**281**	

The overall sample size for subjects in Math, Science, and Business related majors is 643 subjects, 362 male and 281 female. Thus, one can already see that, although more females in the sample received Bachelor's Degrees than males, less majored in these areas. Only 43.7 percent of STEMB majors are female. Also, overall, the STEMB majors make up approximately 41 percent of the sample. Interestingly, there are more females in the sample who majored in the Biological Sciences and Business Management than males. However, much fewer women majored in Computer/Information Sciences, Economics, and Engineering.

Next, I broke down income statistics from the years 2010 (survey year 2011). I chose to use this year because is the most recent of the dataset, and also is after the initial onset of the financial crisis. I broke the income averages down by sex and those who received a degree in one of the STEMB majors. All statistics do not include those with no income in 2010.

Table 3: Summary Income Statistics (in USD) – Income Year 2010

Statistic	Average Income	Median Income	Std. Deviation
Overall	44,967.45	40,000.00	29,411.69
Male	50,548.50	42,500.00	33,009.46
Female	40,693.10	37,000.00	25,537.48
STEMB	52,928.31	45,750.00	32,881.97
Male STEMB	56,475.45	50,000.00	34,963.89
Female STEMB	48,012.98	43,000.00	29,130.92

* Indicates average is statistically significant at 1% level, compared to Overall Average

One can already see that the average income is higher for those with degrees in STEMB majors, and, within the STEMB group, males still have higher wages than females. Overall, females in this sample earn about 80.5 percent of male income, thus the pay gap in my sample is approximately 19.5 percent. According to the Weinberger (1998), in the gender pay gap between all female and male workers with a college degree was about 18 percent. Thus, this dataset does approximately reflect the national wage landscape between genders at the time. Although the standard deviations in the sample are quite high for all statistics, these differences in averages are all significant at the one percent level. In order to prevent statistics from being too skewed by one individual, the NLSY97 takes the average of the top two percent of incomes of the sample and assigns that value as the income number to the same top two percent of earners. The average income is broken down further into specific STEMB majors and by sex (again, only for the Income Year 2010) here:

Table 4: Average Income by STEMB Major and Sex – Income Year 2010

Major	Overall Average	Male Average	Female Average
Biological Sciences	45,869.32	45,383.18	46,183.88
Business Management	49,625.62	54,018.56	44,884.03
Computer Science	57,145.84	55,330.84	66,901.50
Economics	54,356.44	62,296.63	35,300.00
Engineering	69,881.14	70,606.90	67,894.84
Mathematics	48,441.29	43,590.91	57,333.67
Physical Sciences	46,616.88	44,142.86	48,541.11

Examining these numbers shows an interesting trend, the female average is higher than the male average income in about half of these STEMB majors. Thus, it is necessary to break down these results even further to determine where the root of the pay gap lies.

IV. Empirical Specification: Preliminary Results

In "Gender Wage Gaps by College Major in Taiwan: Empirical Evidence from the 1997-2003 Manpower Utilization Survey," Lin applied methodology that I emulate with my investigation, using the pooled Neumark estimator to implement the Oaxaca-Blinder Decomposition. He begins by considering a standard log-wage model:

$$y_i \;=\; \propto^f + \; x_i \;\; \theta^f + \sum_{j=2}^{J} \beta_j^f d_{ij} + \sum_{k=2}^{K} \pi_k^f q_{ik} + \;\varepsilon_i \;\; ;$$

$$i = 1,\ldots,F; j = 1,\ldots,J; k = 1,\ldots,K; \qquad (1)$$

$$y_i \;=\; \propto^m + \; x_i \;\; \theta^m + \sum_{j=2}^{J} \beta_j^m d_{ij} + \sum_{k=2}^{K} \pi_k^m q_{ik} + \;\varepsilon_i \;\; ;$$

$$i = 1,\ldots,M; j = 1,\ldots,J; k = 1,\ldots,K; \qquad (2)$$

where equations (1) and (2) represent the log-wage regressions, respectively, for *F* female and *M* male workers. In the equation, y_i is the log of the hourly wage, x_i is a vector of continuous characteristic regressors, and d_{ij} is a dummy variable equal to one if the *i*th worker's field of study is the *j*th major, and zero otherwise. The q_{ik} captures other sets of dummy variables (Lin, 2010). The next step is to average the fitted values in equations (1) and (2) for all persons with major *j* in order to compute the log-wage for a representative male worker and female worker:

$$\bar{\hat{y}}_j^f = \hat{\propto}^f + \bar{x}_j^f \hat{\theta}^f + \hat{\beta}_j^f + \sum_{k=2}^{k} \hat{\pi}_k^f \bar{q}_{jk}^f \tag{3}$$

$$\bar{\hat{y}}_j^m = \hat{\propto}^m + \bar{x}_j^m \hat{\theta}^m + \hat{\beta}_j^m + \sum_{k=2}^{k} \hat{\pi}_k^m \bar{q}_{jk}^m \tag{4}$$

Here, *x* and *q* are the mean characteristics of a representative female (male) worker with the *j*th major, and a "hat" denotes the estimated counterpart (Lin, 2010). After this is computed, I will decompose the gender pay gap in major *j* into the composition effect and price effect components:

$$\bar{\hat{y}}_j^f - \bar{\hat{y}}_j^m = (\hat{\propto}^f - \hat{\propto}^m) + \left(\hat{\beta}_j^f - \hat{\beta}_j^m\right) + \bar{x}_j^f\left(\hat{\theta}^f - \hat{\theta}^m\right) + \textstyle\sum_{k=2}^{k}(\hat{\pi}_k^f - \hat{\pi}_k^m)\,\bar{q}_{jk}^f + \textstyle\sum_{k=2}^{k}\hat{\pi}_k^m(\bar{q}_{jk}^f - \bar{q}_{jk}^m) + (\bar{x}_j^f - \bar{x}_j^m)\hat{\theta}^m \tag{5}$$

In equation (5), the first four terms on the right hand side are the price components of the gender pay gap, and the last two terms correspond with the composition component of the wage gap within major *j* (Lin, 2010). Thus, Lin defines the gender wage gap within college major *j* as:

$$\hat{g}^j = (\hat{\propto}^f - \hat{\propto}^m) + \left(\hat{\beta}_j^f - \hat{\beta}_j^m\right). \tag{6}$$

(2010). Although I will be following Lin's logic, I plan to use one equation with a dummy variable, g_i for gender, rather than two separate equations. The dummy is equal to one if the ith worker is female, and zero if they are male. Thus, we have:

$$y_i = \propto + g_i\gamma + x_i\theta + \sum_{j=2}^{J}\beta_j d_{ij} + \sum_{k=2}^{K}\pi_k q_{ik} + \sum_{m=2}^{M}\mu_m h_{im} + \varepsilon_i \qquad (7)$$

The gender dummy can also interact with the other dummy variables to reveal more about its link to college major and GPA (in equation (7), interaction terms are represented by h_{im}). In addition, the gender dummy variable makes testing for statistical significance much simpler. Unlike Lin, I am not only investigating the gender gap within a major, but also the unconditional gender gap (gender gap across majors). I will use the following equation to decompose this gap:

$$\bar{\hat{y}}^f - \bar{\hat{y}}^m =$$

$$(\hat{\propto}^f - \hat{\propto}^m) + \left(\bar{x}^f\hat{\beta}^f - \bar{x}^m\hat{\beta}^m\right) + \sum_{j=2}^{J}\left(\beta_j^f\bar{d}_{ij}^f - \beta_j^m\bar{d}_{ij}^m\right) + \sum_{k=2}^{K}\left(\pi_k^f\bar{q}_{ik}^f - \pi_k^m\bar{q}_{ik}^m\right) \quad (8)$$

This equation helps capture the fact that men are more likely than women to choose majors in the STEMB fields. A basic decomposition breakdown for each of the characteristics represented in equation (8) follows, for example:

$$\left(\bar{x}^f\hat{\beta}^f - \bar{x}^m\hat{\beta}^m\right) = \bar{x}^f(\theta^f - \theta^m) + \theta^m\left(\bar{x}^f - \bar{x}^m\right) \qquad (9)$$

Where the first term on the right hand side of equation (9) represents the price effect and the second represents the composition effect of this particular characteristic on the gender pay gap. Here, θ represents the coefficient of the characteristic in the log(income) regression.

My interpretation of Lin's aforementioned empirical model relies on a log(income) regression on a dummy variable for gender (which is equal to one if the subject is female, zero if the subject is male), a dummy variable for college major (equal to one if the subject graduated in that particular major, zero if not), and other continuous and dummy characteristic regressors. To eventually reach a strong regression of this type, I started with more simple regressions to test individual effects, all log(income) regressions for the income year 2010. The first dummy variable I used was not for a specific college major, but for all the STEMB majors in general. I also added a Years Since Graduation variable and Years Since Graduation squared. These variables are only proxies for experience, because they do not account for years spent unemployed between graduation and 2010.

Table 5: Log(Income) Regression on Gender, STEMB, Years since Graduation, Years since Grad Squared

Variables	Coefficients (Robust Std. Errors)	P-value	Regression Constant	R-squared
Gender	-0.182 (0.0427)	0.000***	9.951	0.1014
STEMB Major	0.280 (0.0430)	0.000***	-	-
Years Since Graduation	0.116 (0.0410)	0.005***	-	-
Years Since Graduation Squared	-0.003 (0.0038)	0.410	-	-

*;**;*** represent statistically significant at the 10%, 5%, 1% levels respectively

Gender here is a statistically significant variable, showing that between two people with degrees in a STEMB major who graduated in the same year, but of the opposite sex, the female still earns over 18 percent less than the male. Additionally, having a degree in a STEMB major increases earnings by approximately 28 percent, a very large, and statistically significant, number. This regression also shows that for two people of the same gender with degrees in a STEMB major, an additional year of work experience adds over 11 percent to income.

To include more controls for ability in order to isolate the true effect of gender on income, I added the AFQT variable to my analysis. The AFQT (Armed Forces Qualification Test) is a measure of intellectual ability, in both verbal reasoning and math, which is scored in the range of 0 to 100. Controlling for AFQT also helps to control for selection unobservables because it captures some of the ability bias. The variable included in the following regression indicates the percentile that the subject's AFQT score placed them in.

Table 6: Log(Income) Regression on Gender, STEMB, Years since Graduation, and AFQT Percentile

Variables	Coefficients (Robust Std. Errors)	P-value	Regression Constant	R-squared
Gender	-0.179 (0.0426)	0.000***	9.970	0.1022
STEMB Major	0.273 (0.0426)	0.000***	-	-
Years Since Graduation	0.082 (0.0103)	0.000***	-	-
AFQT Percentile	0.001 (0.0102)	0.171	-	-

*;**;*** represent statistically significant at the 10%, 5%, 1% levels respectively

Here, again, the Gender, STEMB Major, and Years Since Graduation variables are statistically significant, but the AFQT Percentile is not. Therefore, in order to better capture the effect of ability on income, I created dummy variables for those in the 20th, 30th, 40th, 50th, 75th, 80th, and 90th percentile (that equals one if the person did score in that percentile or higher and zero if not) of AFQT scores. The only regression on Gender, the STEMB dummy, and Years Since Graduation with a statistically significant AFQT Percentile dummy follows:

Table 7: Log(Income) Regression on Gender, STEMB, Years since Grad, and AFQT 50th Percentile

Variables	Coefficients (Robust Std. Errors)	P-value	Regression Constant	R-squared
Gender	-0.164 (0.0456)	0.000***	9.956	0.0991
STEMB Major	0.259 (0.0455)	0.000***	-	-
Years Since Graduation	0.080 (0.0110)	0.000***	-	-
AFQT 50th Percentile	0.101 (0.0555)	0.069*	-	-

*;**;*** represent statistically significant at the 10%, 5%, 1% levels respectively

Although not statistically significant at the 5 percent level, the AFQT coefficient in the regression shows that, all other variables being the same, one who scored in the 50th percentile or better on the AFQT has an income of over 10 percent higher than one with a score below the 50th percentile. In addition, the Gender variable here is still statistically significant at the one percent level, indicating that all other variables being equal, a female earns over 16 percent less than a male. To isolate the effects of gender on income within specific college majors, I next grouped some of the majors together in order to create larger sample sizes, and then performed regressions similar to the regression in Table 7. The major groups are Business/Economics, Hard Sciences/Math, Computer Science, and Engineering. For each one, I regressed log (income) on Gender, the major group dummy (equal to one if the subject has a degree in that group, zero if not), Years since Graduation, and each of the AFQT Percentile dummies. The regressions that follow are those with statistically significant AFQT dummies of the highest percentile for each major group.

Table 8: Log(Income) Reg on Gender, Business/Econ Major, Years since Grad, AFQT 80th Percentile

Variables	Coefficients (Robust Std. Errors)	P-value	Regression Constant	R-squared
Gender	-0.202 (0.0455)	0.000***	10.072	0.0828
Business/Econ Major	0.167 (0.0491)	0.001***	-	-
Years Since Graduation	0.082 (0.0113)	0.000***	-	-
AFQT 80th Percentile	0.094 (0.0478)	0.050**	-	-

*;**;*** represent statistically significant at the 10%, 5%, 1% levels respectively

This regression shows that for a female Business or Economics major who graduated in the same year as a male, both with AFQT scores in the 80th percentile, the female earns over 20 percent less than the male counterpart, a very big difference for two people of very similar credentials and ability.

Table 9: Log(Income) Reg on Gender, Engineering Major, Years since Grad, AFQT 50th Percentile

Variables	Coefficients (Robust Std. Errors)	P-value	Regression Constant	R-squared
Gender	-0.196 (0.0455)	0.000***	10.048	0.0895
Engineering Major	0.404 (0.0876)	0.000***	-	-
Years Since Graduation	0.082 (0.0111)	0.000***	-	-
AFQT 50th Percentile	0.101 (0.0556)	0.071*	-	-

*;**;*** represent statistically significant at the 10%, 5%, 1% levels respectively

The results for Engineering majors are less descriptive, because the AFQT 50th percentile variable was the highest percentile for which results were statistically significant, but still indicate that a female engineer who graduated in the same year as a male engineer, both with AFQT scores in the top 50 percent, earns almost twenty percent less.

Table 10: Log(Income) Reg on Gender, CompSci Major, Years since Grad, AFQT 80th Percentile

Variables	Coefficients (Robust Std. Errors)	P-value	Regression Constant	R-squared
Gender	-0.205 (0.0464)	0.000***	10.102	0.0777
Computer Science Major	0.212 (0.0987)	0.032**	-	-
Years Since Graduation	0.084 (0.0114)	0.000***	-	-
AFQT 80th Percentile	0.083 (0.0477)	0.081*	-	-

*;**;*** represent statistically significant at the 10%, 5%, 1% levels respectively

This regression reveals very similar results, regarding gender, to the Business/Economics regression (Table 8). For a female Computer Science major who graduated in the same year as a male, both with AFQT scores in the 80^{th} percentile, the female earns over 20 percent less than the male counterpart, again, a large disparity for two people of similar educational and ability backgrounds.

Table 11: Log(Income) Reg on Gender, Science/Math Major, Years since Grad, AFQT 80th Percentile

Variables	Coefficients (Robust Std. Errors)	P-value	Regression Constant	R-squared
Gender	-0.242 (0.0428)	0.000***	10.133	0.0763
Hard Sciences/ Math Major	0.030 (0.0754)	0.692	-	-
Years Since Graduation	0.084 (0.0109)	0.000***	-	-
AFQT 80th Percentile	0.078 (0.0460)	0.089*	-	-

*;**;*** represent statistically significant at the 10%, 5%, 1% levels respectively

Interestingly, here the Hard Sciences/Math group major dummy is not statistically significant. The Gender variable is though, and shows that for female majors in this group, all else being equal (graduation year, AFQT score above or below the 80^{th} percentile), incomes tend to be about 24 percent lower. Together, all of the aforementioned regressions show that the effect of Gender on income is both large in magnitude, and statistically significant, ranging from about negative 16 to 20 percent.

Finally, to get a deeper understanding of what is driving female major choice in this sample, I ran a probit regression on the STEMB Major dummy based on Gender, Race, AFQT (as a measure for ability), and an interaction between Gender and AFQT. The results are presented in Table 12.

Table 12: Probit Regression for STEMB Major Selection

Variables	Coefficients (Robust Std. Errors)	P-value	Marginal Effect	R-squared
Gender	-0.6798 (0.1392)	0.000***	-0.2602	0.0450
Black	0.0672 (0.0927)	0.469	0.0260	-
Hispanic	-0.1178 (0.1032)	0.254	-0.0447	-
AFQT	2.18E-06 (0.0000)	0.148	8.37E-07	-
Gender/AFQT	1.55E-06 (0.0000)	0.448	5.96E-07	-

*;**;*** represent statistically significant at the 10%, 5%, 1% levels respectively

The only statistically significant variable here is Gender. As expected, being a female has a very negative effect on whether or not a person chooses to major in a STEMB field. Gender is far more important than Race and even ability. Although statistically insignificant and small in marginal effect, especially in comparison to Gender, AFQT score does have the expected positive sign. Thus, it has been established that Gender is the main driver of college major choice into a STEMB field, an interesting fact to keep in mind as I progress to more detailed results in the next section.

V. Empirical Specification: Final Results

To examine the effects of gender, undergraduate major and experience, and ability on income, I put all of the aforementioned variables (including dummies for all but one of the AFQT ranges, to prevent multicollinearity) into one regression. In addition, as an additional ability measure, I added a dummy for whether or not the subject's cumulative college GPA was a 3.0 or above (equal to one if so, zero if not) and an interaction term between Gender and this dummy. The results are shown in Table 13.

In this regression, the STEMB major coefficient is statistically significant and of very high magnitude, STEMB majors make almost 30 percent more than non-STEMB majors. The 3.0 GPA coefficient is also statistically significant at the 10 percent level and indicates that having a GPA of 3.0 or higher raises income by over 11 percent. The Years Since Graduation variable is also statistically significant and of the expected sign.

The interaction terms, although not statistically significant, have interesting point estimates. The Gender and STEMB major interaction has a very small magnitude, which suggests that both females and males have the same return for majoring in a STEMB field. On the other hand, the Gender and 3.0 GPA dummy interaction has a higher magnitude than the GPA dummy itself and is in the opposite direction. This indicates that females receive no return from earning a high GPA, whereas males see a jump in their income.

Most importantly, note that the Gender coefficient is now statistically insignificant, and has decreased in magnitude to show that females earn only 8 percent less than males. This result suggests that, when majoring in a STEMB field, GPA, Years since Graduation, and AFQT ability measures are controlled for, only about 8 percent of the gender pay gap remains unexplained.

Table 13: Log(Income) Regression for Income Year 2010

Variables	Coefficients (Robust Std. Errors)	P-value	Regression Constant	R-squared
Gender	-0.084 (0.1039)	0.417	9.8261	0.1130
STEMB Major	0.294 (0.0601)	0.000***	-	-
Gender/STEMB	-0.023 (0.0856)	0.786	-	-
3.0 GPA	0.112 (0.0649)	0.085*	-	-
Gender/3.0 GPA	-0.114 (0.1061)	0.284	-	-
Years since Grad	0.112 (0.0408)	0.006***	-	-
(Yrs since Grad)^2	-0.003 (0.0038)	0.422	-	-
AFQT 20-29 Percentile	-0.190 (0.1225)	0.122	-	-
AFQT 30-39 Percentile	0.121 (0.0987)	0.222	-	-
AFQT 40-49 Percentile	0.059 (0.0869)	0.495	-	-
AFQT 50-74 Percentile	0.075 (0.0745)	0.314	-	-
AFQT 75-80 Percentile	0.086 (0.0817)	0.292	-	-
AFQT 80-89 Percentile	0.162 (0.0670)	0.016**	-	-
AFQT 90+ Percentile	0.010 (0.0726)	0.894	-	-

*;**;*** represent statistically significant at the 10%, 5%, 1% levels respectively

I also wanted to investigate the specific connection between gender and college major further, and so I added interaction variables between Gender and each of the specific major dummies, instead of just the overall STEMB major dummy. The results are shown in Table 14.

Table 14: Log(Income) Regression for Income Year 2010

Variables	Coefficients (Robust Std. Errors)	P-value	Regression Constant	R-squared
Gender	-0.097 (0.1039)	0.346	9.832	0.1220
Business/Econ	0.268 (0.0687)	0.000***	-	-
Gender/Business	-0.048 (0.0974)	0.622	-	-
Engineering	0.447 (0.1179)	0.000***	-	-
Gender/Engineering	0.252 (0.1623)	0.121	-	-
Hard Sciences	0.085 (0.1009)	0.397	-	-
Gender/Hard Sciences	0.086 (0.1509)	0.567	-	-
Computer Science	0.250 (0.1109)	0.025**	-	-
Gender/CompSci	0.401 (0.2102)	0.057*	-	-
3.0 GPA	0.114 (0.0643)	0.077*	-	-
Gender/3.0 GPA	-0.109 (0.1051)	0.299	-	-
Years since Grad	0.116 (0.0409)	0.005***	-	-
(Yrs since Grad)^2	-0.003 (0.0038)	0.370	-	-
AFQT 20-29 Percentile	-0.190 (0.1232)	0.124	-	-
AFQT 30-39 Percentile	0.118 (0.1002)	0.238	-	-
AFQT 40-49 Percentile	0.053 (0.0871)	0.543	-	-
AFQT 50-74 Percentile	0.077 (0.0748)	0.305	-	-
AFQT 75-80 Percentile	0.082 (0.0817)	0.315	-	-
AFQT 80-89 Percentile	0.160 (0.0681)	0.018**	-	-
AFQT 90+ Percentile	-0.002 (0.0729)	0.981	-	-

*;**;*** represent statistically significant at the 10%, 5%, 1% levels respectively

In this regression, all of the STEMB major coefficients are statistically significant, except for the hard sciences and math coefficient. All of the majors have the expected sign and magnitude, with Engineers having the highest return on their choice of major, increasing wages by almost 45 percent. The 3.0 GPA dummy variable is statistically significant at the 10 percent level, with having a GPA of 3.0 or higher increasing wages by about 11 percent. The Years since Graduation and Years since Graduation squared variables have the expected signs, and the statistically significant Years since Graduation variable indicates that each year out of college, a proxy for each year of experience, adds almost 12 percent to one's wages. The AFQT variables are not statistically significant except for the 80th to 89th percentile. Finally, note that with the addition of all of the interaction coefficients, the gender variable is no longer statistically significant. However, it still has a negative sign and a magnitude of 0.097, suggesting that about 10 percent of the gender pay gap remains unexplained.

Examining the interaction coefficients offers more insight into the connection between the gender pay gap and college experience. The only interaction coefficient that is statistically significant at the 10 percent level or better is the Gender and Computer Science major interaction. Still, it is interesting to note that the only college major and gender interaction that is negative is for the Business and Economics majors. Thus, the results suggest that for the STEMB majors, with the exception of the business group, females actually have a higher proportionate return for choosing this major than males. However, taking into account the negative Gender dummy coefficient of -0.097, the return is not as high as the interaction coefficients suggest.

The last interaction variable to note is the Gender and 3.0 GPA dummy interaction variable. Although it is not statistically significant, it is negative and of almost the exact opposite magnitude as the 3.0 GPA dummy alone. This suggests, especially when taken into account with the negative coefficient of the Gender dummy, that, all else being equal, females do not see the same return of a GPA above 3.0 in their future income that their male classmates do.

A key takeaway from the regression results in Table 14 is that once experience, AFQT, GPA, and college major has been controlled for, the Gender coefficient changes dramatically from that in the earlier regressions. Firstly, it becomes statistically insignificant. Secondly, compared to the earlier results, the gender effect falls by about a half to a third, as measured by the point estimates. This suggests that controlling for these factors renders Gender unimportant.

Now that the effects of gender, experience, and ability on income have been isolated by major and examined, I put together all of these variables, along with other important demographic and industry indicators, into one log(income) regression. The first new addition is a dummy for whether or not the subject has a child (equal to one if they have one or more children, zero if they have not). Another dummy variable included is one for marital status, one if the subject is married or lives with a significant other, zero if not. I also added individual dummies for the Black and Hispanic race indicators. There is some ambiguity in the possible indications of race available in the NLSY97 survey (the only options are Black, Hispanic, Mixed Race (Non-Black/Non-Hispanic), or Non-Black/Non-Hispanic), which leaves some racial groups without a clear classification. Thus, isolating the Black and Hispanic options will make the results more clear and easy to interpret. I also felt that it was important to isolate the effects of job industry on income. The industries I have isolated are the Finance/Insurance industry, Education, Manufacturing, and Retail industries. I wanted to delve into the issue of gender further by adding some family life interaction variables as well. Therefore, I created interaction terms (with the values multiplied together as the interaction) for the Gender and Child dummies and the Gender and Marital Status dummies. The results of this regression are in Table 15.

Interestingly, the child and race dummies are not statistically significant, and have very small coefficients. The small coefficients of the race dummies can potentially be explained by the fact all subjects do have a bachelor's degree, and the child dummy could be a result of including an interaction between Child and Gender. A male with a child is likely to work to earn more money to support that child, while a female may leave the workforce, and these effects could be offsetting each other. The coefficient for the Gender and Child interaction term in the regression shows that having a child has a highly negative impact on earnings for females. About 32 percent of females in my sample have children, so this interaction term is not picking up the effects of the gender variable. The large magnitude of the Gender and Child interaction is consistent with the findings of Waldfogel (1998), who determined that the wage gap between females with children and males without was almost 27 percent in 1994. On the other hand, the marital status dummy is statistically significant, but the interaction term is not. The magnitude of the marital status dummy is very large, suggesting that, all else being equal, a married man earns 20 percent more than an unmarried man. Although the interaction term isn't significant, it's negative sign indicates that this effect is offset quite a bit if the subject is a woman. This is consistent with the findings of Donald and Hamermesh (2004), who found that the wage gap between a single man and woman is significantly less than that between a married man and a married woman. Nonetheless, all of these variables show that family choices, rather than discrimination against women, have a very large impact on income.

The major group coefficients are similar to those in the earlier results presented in Table 14. All of the STEMB major dummies have positive coefficients, with Engineering, unsurprisingly, with the highest magnitude. All but the Hard Sciences group are statistically significant at the 5 percent level or better. Engineering majors earn about 40 percent more than non-Engineers, all else being equal. Although they are not statistically significant, examining the magnitudes of the major interaction terms reveal that in Engineering, the Hard Sciences, and Computer Science, females actually get more of a proportionate return for choosing those majors than males. On the other hand, in Business and Economics, females earn less than their male classmates. Lastly, the Gender and 3.0 GPA dummy interaction variable is interesting. Even though neither the GPA dummy nor the interaction are statistically significant, they are of equal and opposite magnitude, which suggests that a female receives little to no return from maintaining a GPA of above a 3.0, whereas a male receives income of almost ten percent more. My results are consistent with those of Conger and Long (2010), who found that college major choice has a much more significant impact on earnings than GPA. In my study, a GPA of above 3.0 only raises one’s earnings by about 10 percent, whereas a major in Business/Economics, Engineering, or Computer Science increases wages by over 20 percent.

In addition, unsurprisingly, teachers, all else being equal, tend to make over 11 percent less than other subjects, while those in the financial industry make about 12 percent more. Subjects in the manufacturing industry have slightly lower wages, but this difference is not statistically significant. Lastly, those who work in Retail, all else being equal, earn almost 17 percent less than other subjects, and this result is statistically significant at the 5 percent level.

For proxies for experience and ability, the Years since Graduation variable is statistically significant, with each additional year of experience increasing wages by about 11 percent, and both it and the Years since Graduation squared variable have the expected signs. The only statistically significant ability measure is the AFQT 80^{th} – 89^{th} percentile dummy, where there is about a 15 percent jump in income. The AFQT 20^{th}-29^{th} percentile dummy has the expected negative sign for its coefficient.

It is important to note that the Gender coefficient, although statistically insignificant and of small magnitude, is now positive. This indicates that the gender pay gap can be explained by various demographic indicators, college major choice, job industry, and certain ability measures. These results are consistent with Lin's (2010) findings in Taiwan, which show that when controlling for job industry and other indicators, the gender pay gap becomes statistically negligible.

Table 15: Log(Income) Regression for Income Year 2010

Variables	Coefficients (Robust Std. Errors)	P-value	Regression Constant	R-squared
Gender	0.033 (0.1022)	0.750	9.788	0.1458
Marriage	0.220 (0.0688)	0.001***	-	-
Gender/Marriage	-0.141 (0.0948)	0.137	-	-
Child	0.074 (0.0707)	0.294	-	-
Gender/Child	-0.228 (0.0981)	0.020**	-	-
Black	0.019 (0.0591)	0.743	-	-
Hispanic	0.021 (0.0694)	0.757	-	-
Business/Econ	0.225 (0.0700)	0.001***	-	-
Gender/Business	-0.036 (0.0981)	0.715	-	-
Engineering	0.400 (0.1588)	0.001***	-	-
Gender/Engineering	0.244 (0.1570)	0.120	-	-
Hard Sciences	0.044 (0.1206)	0.658	-	-
Gender/Hard Sciences	0.121 (0.1484)	0.417	-	-
Computer Science	0.250 (0.1064)	0.019**	-	-
Gender/CompSci	0.358 (0.2140)	0.095*	-	-
3.0 GPA	0.095 (0.0624)	0.130	-	-
Gender/3.0 GPA	-0.095 (0.1059)	0.371	-	-
Years since Grad	0.113 (0.0401)	0.005***	-	-
(Yrs since Grad)^2	-0.003 (0.0038)	0.360	-	-
Finance Industry	0.120 (0.0620)	0.052*	-	-
Manufacturing Industry	-0.055 (0.0925)	0.554	-	-
Teaching Industry	-0.115 (0.0533)	0.031**	-	-
Retail Industry	-0.166 (0.0771)	0.032**	-	-
AFQT 20-29 Percentile	-0.184 (0.1213)	0.130	-	-
AFQT 30-39 Percentile	0.105 (0.0978)	0.285	-	-

*;**;*** represent statistically significant at the 10%, 5%, 1% levels respectively

Table 15 Continued: Log(Income) Regression for Income Year 2010

Variables	Coefficients (Robust Std. Errors)	P-value	Regression Constant	R-squared
AFQT 40-49 Percentile	0.037 (0.0871)	0.667	-	-
AFQT 50-74 Percentile	0.064 (0.0747)	0.388	-	-
AFQT 75-80 Percentile	0.065 (0.0820)	0.426	-	-
AFQT 80-89 Percentile	0.148 (0.0681)	0.030**	-	-
AFQT 90+ Percentile	-0.007 (0.0756)	0.925	-	-

*;**;*** represent statistically significant at the 10%, 5%, 1% levels respectively

Thus, my results show that once educational choice, industry choice, and family considerations are accounted for, very little determination of income seems to be left to gender alone, in either a statistical sense or in an empirical sense. The initial 16 to 20 percent range from the first regressions is reduced to just over 3 percent, and is not statistically significant.

Finally, to decompose the gender pay gap into the price and composition effects of the Oaxaca-Blinder Decomposition, I used the regression presented in Table 16. For simplicity in the Oaxaca Blinder breakdown, I only included the STEMB major dummy, 3.0 GPA dummy, Years since Graduation, and AFQT score, plus Gender interacted with all of those. In this way, the effects of college experience on this decomposition are more apparent.

Table 16: Log(Income) Regression for Income Year 2010

Variables	Coefficients (Robust Std. Errors)	P-value	Regression Constant	R-squared
Gender	-0.004 (0.1554)	0.979	9.8373	0.1070
STEMB Major	0.295 (0.0658)	0.000***	-	-
Gender/STEMB	-0.035 (0.0914)	0.700	-	-
3.0 GPA	0.118 (0.0729)	0.106	-	-
Gender/3.0 GPA	-0.120 (0.1046)	0.252	-	-
Years since Grad	0.103 (0.0153)	0.000***	-	-
Gender/Yrs since Grad	-0.036 (0.0204)	0.076*	-	-
AFQT	-1.80E-07 (0.0000)	0.865	-	-
Gender/AFQT	1.82E-06 (0.0000)	0.201	-	-

*;**;*** represent statistically significant at the 10%, 5%, 1% levels respectively

The regression shows that a STEMB Major and Years since Graduation seem to be the most significant factors in determining income, and thus will most likely be the main drivers in differences in the price and composition effects. Using the methodology outlined at the beginning of this section and the regression coefficients above, I obtained the following results. The difference in log of income between males and female earners in 2010 is approximately 0.231, with males having higher income, as expected. This difference is statistically significant at the 1 percent level. The price effect is 0.176. This indicates that if women had the same characteristics as men, the pay gap would be about 17.6 percent. The composition effect is 0.055, suggesting that if one applied the male coefficients to female characteristics, or female "skills," the gender gap would only be 5.5 percent. Thus, when breaking down female wages into price and composition effects based on college experience, the larger magnitude of the price effect indicates that the gender pay gap is mainly driven by the fact that the return of certain academic choices in college is different for females than for males. Breaking down the price and composition effects further, the STEMB major variable accounts for nearly all of the composition portion of the gap. It contributes 0.062 to this effect, while AFQT adds another 0.007, and Years since Graduation subtracts 0.014. The effect of GPA is negligible. Thus, if females were to choose STEMB majors in the same proportion as males, the composition effect of the decomposition would almost be entirely eliminated. This shows that the fact that females are less likely to major in a STEMB field is the main difference that contributes to the composition portion of the gap, which as a whole accounts for approximately 23.8 percent of the gender pay gap. Therefore, the choice of a STEMB major, as it is the main contributor to the composition effect, can be estimated to account for nearly one quarter of the gender pay gap.

On the other hand, about 76.2 percent of the gender pay gap is attributed to the price effect. In other words, this portion of the gap exists because female “skills” are priced differently. Yet, the coefficient for choice of a STEMB major does not contribute significantly to this gap. It only adds about 0.010 to the price effect. The main driver of this effect is the “price” of the Years since Graduation variable, which adds 0.191 to the price effect. The 3.0 GPA dummy also adds 0.098 to the effect (the AFQT subtracts from the effect, getting us to the 0.176 number). In other words, the value of a STEMB major is relatively equal for males and females, which is consistent with the results earlier in this section. On the other hand, the “price” of each additional year since graduation is not nearly as high for females as it is for males. In addition, the return of a 3.0 or better GPA for females is also lower than it is for males, again consistent with my earlier findings. Further investigation is needed to determine the reasons for these differences in "price" of GPA and Years since Graduation, which is beyond the scope of this paper.

VI. Conclusion

One of the most important factors in determining future income is college experience. By investigating the link between college major choice, GPA, and future income, I have found that college major selection is an important component of the gender pay gap. When controlling for ability measures and years of experience in the working world, my results indicate that majoring in a field in Business, Economics, Computer Science, or Engineering is a statistically significant indicator of a higher future income, for both females and males. Women who major in these fields receive significantly higher wages than women who do not, even if the women who majored in the humanities had higher GPAs. The Females who choose STEMB majors do not receive a statistically significant lower return than males. In fact, my results indicate that, in all STEMB fields except Business and Economics, females actually may receive a higher return from majoring in these fields than males, especially in the Computer Science field. Thus, if more females were to choose majors in the STEMB disciplines, perhaps we could come closer to closing the gender pay gap.

My results do not show a particularly strong link between college GPA and future income. A cumulative GPA of 3.0 or higher suggests higher income of about 10 percent, but the results are not statistically significant enough to conclusively confirm this fact. Yet, the results do suggest that females do not receive as high of a return in future income from maintaining a high GPA (specifically, above a 3.0). More investigation is needed to make a strong conclusion on this point.

Furthermore, isolating certain demographic indicators, ability measures, job industry selection and college major choice can help to nearly fully explain the gender pay gap. In Table 15, when controls were added for various family indicators, such as marital status and birth of children, race, and also for job industry, the gender dummy variable no longer exhibited a negative coefficient and is statistically negligible.

Lastly, breaking down the gender pay gap into the price and composition effects of the Oaxaca-Blinder Decomposition based on various college experience indicators reveals that about three quarters of the gap can be attributed to the price effect. That is, most of the gender pay gap is a result of the fact that female skills are not "priced" as high as male skills. However, a degree in a STEMB major has about the same value for females as for males. GPA, on the other hand, is "priced" much higher for males than it is for females. The composition effect does still account for one quarter of the gender pay gap, and nearly all of this effect is attributed to the STEMB major characteristic. Thus, if females and males did choose STEMB majors in the same proportion, the gender pay gap would be significantly smaller.

Although the gender pay gap in the United States has many different causes, not all related to undergraduate education, my study into its links to college experience has revealed many interesting results. It is apparent that the composition of males and females in different college majors has a significant impact on the gap. Thus, if more females begin to choose STEMB majors in college, we will take large strides in closing the gender pay gap.

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