Do Computer Science graduates earn higher yearly incomes compared to other undergraduate majors?

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## 

## Abstract

This paper uses the Current Population Survey data to examine whether college graduates with a bachelor’s degree in Computer Science earn higher annual income than graduates with other majors or people without a college degree. I will estimate a variety of variables to mitigate the effect of unobserved variables that might be correlated with the yearly income of the observations. The result suggests that Computer Science and Engineering majors make more than other majors in general. This study also discusses the results related to the gender and racial pay gap, as well as the effect of work experience and educational attainment.

## Introduction

In recent years, the demand for technical workers, especially in software engineering has always been on the rise, to the extent that the United States companies need to hire foreign workers to adapt to their business growth. By numbers, there were more than 200,000 H1-B visa holders in 2002, accompanied by more than 20$ million worth of scholarship money given yearly to undergraduate computer science, engineering, and math majors, according to data from the National Science Foundation (Mervis, 2000). The number of foreign workers authorized to work in the US increased to nearly 600,000, according to the 2019 USCIS H1-B Population Survey. With the provided context, the demand for workers with at least a bachelor’s degree is on the rise, so the goal of this study is to observe how an education in the mentioned field will pay off in the future.

## Literature Review and Theoretical Analysis

This literature review will discuss the body of research related to the research question of this paper: What are the earnings return for a computer science graduate, compared to other majors? To do so, I will first discuss the recent publications on this subject and briefly present results from previous studies. Then, this review will introduce the independent variables that can influence the answer to the research question, explaining why these factors are relevant and their characteristics. Then, I will discuss the theoretical framework applied to the study to develop the regression model.

As mentioned above, the return on education has long been a topic of interest for researchers. In his study on such topics, Arcidiacono (2004) points out that the return on majoring in natural science and business is generous. Arcidiacono also found a strong relationship between undergraduate GPA and yearly earnings. For all majors in general, going from 2.5 to 3.0 will increase yearly earnings by 5%, especially for business majors the increase is 13%. However, regarding natural science majors, he notes that majors such as biology might have higher grades in college, but not necessarily be well-compensated in the workforce, which leads to depressing coefficients on yearly earnings (Arcidiacono, 2004).

The racial income gap is also relevant in this context. Recent studies suggest that the educational attainment gap between Blacks and Whites is narrowing, especially since the rate of college attendance for African Americans increases more than that of White-Americans–4.4% to 22.5% compared to 11.3% to 32.8% in the same period (McClough and Benedict, 2017). However, this increase does not necessarily strongly affect narrowing the race pay gap. McClough and Benedict (2017) conclude that African American college students, on average, graduate with academic majors associated with lower-paying occupations. These researchers also point out the underlying reason for this conclusion, which is that Black high school graduates are academically less prepared than Whites coming to college. That said, the number of Black male students switching from rigorous majors such as natural sciences, engineering, economics, or business to less demanding majors like social sciences and humanities is 54% compared to 8% of White males. However, these researchers suggest that students with higher ability will be able to complete rigorous coursework associated with higher pay, regardless of race or gender (McClough and Benedict, 2017).

On the other hand, it is evident that gender does play a role in determining income after graduation. Joy (2003) points out that academic-related variables such as major, grades, or institution attended do influence the gender salary gap, but the effect of the said variables is not as substantial as labor market-related variables. However, Joy also suggests that academic majors and the labor market are only a part of the story, as 75% of the gender wage gap remained unexplained. This proves that the gender pay gap remains debatable, as many previous studies failed to produce a consistent answer to this problem. Krueger (1993) points out that while the gender pay gap is narrowing, for the most part, researchers have not been able to fully explain the earnings gap, regardless of controlling for factors such as labor supply, work experience, or training (Daymont, Andrisani, 1984). Therefore, gender needs to be included as a control to improve the regression coefficients.

Echoing the above discussion on the effect of race and gender on annual income after college, years of educational attainment are added for its relevance. On the other hand, years of work experience are derived using this variable, and I will explain by what formula experience is calculated as I continue my analysis.

To further improve the regression results, work experience is also added as a control independent variable. Since the relationship between income and work experience is non-linear, a quadratic transformation will be applied, meaning that the squared of experience is added to the model equation.

Since the purpose of this study revolves around observing the monetary return on education, I must take into consideration the time value of money, as the investment in education yields returns in the future. Then, I need to consider the present value (in US Dollars) of the return on education after graduation, in this case, is the income of graduates. The earnings function framework is the chosen solution to this problem. This theoretical framework was developed by Mincer (1958) and explains that the distribution of personal income, which is our interest, only approximates normality and is symmetric when it is transformed into a logarithmic distribution. That is, personal income differentials are described via a random shock process, which “generates a log-normal distribution if applied to the logarithms of income rather than to income itself” (Mincer, 1958, p. 283). Then, the income differentials will be interpreted as a percentage-point difference, rather than an absolute value of income.

## Empirical Analysis

### A. The Data

#### **i. Provide sources on all variables**

##### **Dependent variable:**

Yearly Income (US Dollars/year): I choose to measure yearly income over hourly pay for several reasons. The first reason is to be consistent with other studies on annual income. More importantly, using yearly income allows us to control full-time workers. An hourly-based wage fails to indicate whether a person is working full-time or not. This paper decides the threshold for full-time workers is an annual income of over $20,000. Therefore, any observations with INCWAGE less than 20000 will be omitted. Another reason is that low INCWAGE values when being applied to logarithmic functional form will yield erroneous results which can potentially distort the regression results. Additionally, college graduates will likely be paid on a salaried basis instead of an hourly basis. That is, if a graduate works as a software developer, contractor, engineer, or in managerial roles, he or she will be paid on a salary basis, which includes a fixed amount of base salary, adding bonuses, commissions, stock options, equity, etc. No amount of overtime work will be recorded on a salary basis. Therefore, using yearly total compensation is a more liable measure since it corrects for fluctuations in the annual income of a worker.

##### **Independent variables:**

1. EducYears (years): Re-coded from EDUC. EducYears ranges from 9 to 18; grade 1 to 9 is aggregated to 9 years of education and having more than 18 years of education is categorized as 18.
2. Experience and Experience Squared (years): Years of experience (Experience) will be calculated by subtracting years of education attainment (EducYears) and 6 (from 0 to 6 years before the first year of schooling) from AGE
3. Race: Re-coded from RACE. Aggregated into Black, White, Asian, and Other Races. The purpose of aggregating is to study the racial income gap discussed in previous studies.
4. Majors (categorized into CS and other fields): For this paper, different majors will be aggregated into several categories, which are Computer Science, Natural Sciences, Social Sciences, Engineering, Business, Arts, Other Majors, and No College Degrees. Then, Computer Science will be used as a dummy variable base case to which other aggregated major groups can be compared.
5. Double majors: The question of whether a graduate double majored in college is also taken as a control to improve the regression result.

**ii. Summary Statistics**

This part of the study will present the summary of the dataset while making no conclusion from the presented tables. The reason is that these are aggregated data, which is a combination of different factors that affect the result. For example, presenting the summary of income after graduation of CS and non-CS graduates fails to control the effect of gender, race, and other academic majors. Then, this section only provides a brief overview of the dataset. Having said that, the regression results will the relationship between different variables in their contribution to yearly income.

1. Income after graduation of CS and non-CS graduates

Table I: Means of wage and salary income on CS and EducYears

| CS

EducYears | 0 1 | Total

-----------+----------------------+----------

9 | 42997.585 . | 42997.585

10 | 46118.033 . | 46118.033

11 | 45250.321 . | 45250.321

12 | 51691.47 . | 51691.47

13 | 58779.428 . | 58779.428

14 | 58763.69 . | 58763.69

16 | 85257.991 105654.55 | 86224.722

18 | 113711.9 137023.55 | 114445.03

-----------+----------------------+----------

Total | 73160.494 115513.38 | 73948.902

Table I demonstrates the average income of CS graduates compared to those without a CS degree (both attained at least 16 years of education), and others without a college degree. Initially, the dataset is consistent with the assumption that more education means more income. We can see an income gap of roughly $20,000 between CS and non-CS graduates. However, a college degree is still worth investing in—college grads make $35,000 more than those without a degree.

1. The gender pay gap

Table II: Means of wage and salary income on Male and EducYears

| Male

EducYears | 0 1 | Total

-----------+----------------------+----------

9 | 36812.251 45828.162 | 42997.585

10 | 33866.176 50851.705 | 46118.033

11 | 42125.253 46702.817 | 45250.321

12 | 43203.629 56960.073 | 51691.47

13 | 49051.173 66399.445 | 58779.428

14 | 51226.369 66991.683 | 58763.69

16 | 69657.03 102122.13 | 86224.722

18 | 93091.648 138282.59 | 114445.03

-----------+----------------------+----------

Total | 63032.612 83126.126 | 73948.902

Table II above demonstrates the average income of each gender for every year of education. The gender income gap increases for people with more education. Specifically, men with a college degree make about $30,000 more than women of the same education level. The numbers are even higher for post-graduate levels—$45,000 less pay for women. While the results are surprising, it is also important to note these are only aggregated numbers, meaning that they do not account for the difference in academic majors, performance, race, and other variables that might have an effect.

1. Racial pay gap in Computer Science

Table III: Means of wage and salary income on CS and White

| White

CS | 0 1 | Total

-----------+----------------------+----------

0 | 64591.321 76749.477 | 73160.494

1 | 115754.24 115363.79 | 115513.38

-----------+----------------------+----------

Total | 65820.598 77380.083 | 73948.902

The table above shows the average income of CS and non-CS graduates by race. While there is an evident income disparity between non-CS graduates, the pay between White and non-White Computer Science graduates is effectively the same. The discussion of the regression result will go into detail the effect of race on income.

1. Gender income gap in Computer Science

Table IV: Means of wage and salary income on CS and Male

Male

CS | 0 1 | Total

-----------+----------------------+----------

0 | 62750.029 82067.23 | 73160.494

1 | 93256 122059.66 | 115513.38

-----------+----------------------+----------

Total | 63032.612 83126.126 | 73948.902

Table IV above illustrates the gender income gap among Computer Science graduates. While it is evident that graduating with a CS degree leads to more annual income, there exists a noticeable pay gap between males and females. The regression results will contribute to the discussion of the gender income differential by controlling for other factors such as years of work experience, education, and race.

B. Presentation and Interpretation of Results

##### **Regression Results**

This portion of the study will report the Ordinary Least Squared regression result of regression the natural log of Yearly Income on Majors dummy (CS as the base case), Double Majors dummy, Race dummy (White as the base case), Years of Education and Work Experience.

Table V: OLS Regression Result. Independent Variable: ln(INCWAGE)

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | (1) | (2) | (3) | (4) |
|  | lnINCWAGE | lnINCWAGE | lnINCWAGE | lnINCWAGE |
| NaturalScience | -0.122\*\*\* | -0.0970\*\*\* | -0.0933\*\*\* | -0.183\*\*\* |
|  | (0.0219) | (0.0228) | (0.0229) | (0.0233) |
|  |  |  |  |  |
| SocialScience | -0.273\*\*\* | -0.234\*\*\* | -0.233\*\*\* | -0.327\*\*\* |
|  | (0.0212) | (0.0220) | (0.0221) | (0.0224) |
|  |  |  |  |  |
| Engineering | -0.00210 | 0.0317 | 0.0341 | 0.0447 |
|  | (0.0232) | (0.0242) | (0.0243) | (0.0248) |
|  |  |  |  |  |
| Business | -0.111\*\*\* | -0.105\*\*\* | -0.105\*\*\* | -0.158\*\*\* |
|  | (0.0218) | (0.0227) | (0.0228) | (0.0233) |
|  |  |  |  |  |
| Arts | -0.321\*\*\* | -0.336\*\*\* | -0.335\*\*\* | -0.416\*\*\* |
|  | (0.0285) | (0.0297) | (0.0299) | (0.0304) |
|  |  |  |  |  |
| OtherMajors | -0.280\*\*\* | -0.298\*\*\* | -0.305\*\*\* | -0.366\*\*\* |
|  | (0.0284) | (0.0296) | (0.0297) | (0.0303) |
|  |  |  |  |  |
| NoDeg | -0.274\*\*\* | -0.638\*\*\* | -0.657\*\*\* | -0.703\*\*\* |
|  | (0.0231) | (0.0212) | (0.0212) | (0.0216) |
|  |  |  |  |  |
| DoubleMajor | 0.0736\*\*\* | 0.0652\*\*\* | 0.0694\*\*\* | 0.0715\*\*\* |
|  | (0.0125) | (0.0130) | (0.0131) | (0.0134) |
|  |  |  |  |  |
| Male | 0.254\*\*\* | 0.239\*\*\* | 0.242\*\*\* |  |
|  | (0.00560) | (0.00581) | (0.00584) |  |
|  |  |  |  |  |
| Hispan | -0.0731\*\*\* | -0.134\*\*\* |  |  |
|  | (0.0109) | (0.0113) |  |  |
|  |  |  |  |  |
| Black | -0.166\*\*\* | -0.169\*\*\* |  |  |
|  | (0.0101) | (0.0105) |  |  |
|  |  |  |  |  |
| Asian | 0.00348 | -0.0174 |  |  |
|  | (0.0109) | (0.0114) |  |  |
|  |  |  |  |  |
| OtherRaces | -0.0294\*\* | -0.0462\*\*\* |  |  |
|  | (0.0105) | (0.0109) |  |  |
|  |  |  |  |  |
| EducYears | 0.102\*\*\* |  |  |  |
|  | (0.00260) |  |  |  |
|  |  |  |  |  |
| Exp | 0.0353\*\*\* |  |  |  |
|  | (0.00103) |  |  |  |
|  |  |  |  |  |
| Exp2 | -0.000541\*\*\* |  |  |  |
|  | (0.0000205) |  |  |  |
|  |  |  |  |  |
| Constant | 9.142\*\*\* | 11.28\*\*\* | 11.25\*\*\* | 11.44\*\*\* |
|  | (0.0492) | (0.0214) | (0.0213) | (0.0213) |
| Observations | 41364 | 41364 | 41364 | 41364 |

Standard errors in parentheses

\* *p* < 0.05, \*\* *p* < 0.01, \*\*\* *p* < 0.001

##### **Interpretation of Results**

The regression results indicate that there is an overall narrowing in the income gap between those with non-CS majors, without a college degree, or double majors compared and Computer Science graduates as more control variates such as gender, educational attainment, experience, and race are added.

That is, while those without a bachelor’s degree will earn less than those with a CS degree, the pay gap narrows from 50% (exp(-0.703)-1) to 24% (exp(-0.274)-1).

However, it is not the same as Engineering degrees. The results show that from earning 4% (exp(-0.0447)-1) more than CS grads, engineers earn 0.21% (exp(-0.0021)-1) less after controlling for the mentioned factors.

While Natural Science majors are often associated with similar income levels as that in Computer Science or Engineering, the results yield a different narrative. That is, Natural Science majors earn 11% less than CS majors, holding other variables constant. This result is consistent with Arcidiacono’s finding in 2004 that majors such as biology might be underpaid regardless of high college GPA.

Other control variables demonstrate expected results. For EducYears, one additional year of education yields roughly an 11% increase in yearly income (exp(0.102)-1). The same tendency is realized for years of experience, as the increase is about 3% (exp(0.0353)-1).

Conversely, the coefficients on gender yield comparable results. Despite controlling for all aforementioned factors, the figures remain relatively unchanged, with only a 2% increase when controlled—27% (exp(0.239)-1) to 29% (exp(0.239)-1). This result stays consistent with the debate on the gender pay gap put forth by previous studies—a substantial portion of the gender pay gap remains unexplained.

On the other hand, the regression reports positive results regarding the income disparity between races. That is, other races other than White continue narrowing the income gap as more variables are considered. While Asians make more than Whites when considering education and experience, the numbers for Blacks remain stagnant.

## Conclusion

In conclusion, I found out that CS and Engineering are among the highest-paid occupations. However, Natural Science is underpaid compared to CS and Engineering, consistent with previous studies pointing out this issue (Arcidiacono, 2004). Continuing the discussion raised by previous studies, the gender pay gap is unexplained by factors such as majors, education, work experience, and race. Additionally, I found out that the racial pay gap is narrowing when additional controls are included. These results suggest that the demand for Computer Science-related discipline is still on the rise, and the overall return on investment for education is generous.

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