***Effect of Education on Yearly Compensation- Evidence from Apple and Amazon companies***

***Econometrics Presentation***

***Presented by***

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**Introduction**

If we believe compensation experts, in the United States, annual compensation may be 25% to 40% higher than the basic salary of an individual (CNN Business, 2021). Annual compensation is the sum of base salary and other benefits, or incentives provided by the employers to the employees.

What is the reason behind discrepancy in annual compensation of an employee in any economy? Is it due to innate qualities like skills and education? Or, is it due the nature of the company? what will be the effect on our yearly compensation if we choose carrier in a tech company and non-tech company, given our education level? These questions have always remained as an intriguing questions which always attracts more and more investigations. So, to distinguish between these scenarios is crucial, especially considering its policy implications.

**Literature Retrospect**

Even if we see the data published by US Bereau of Labor Statistics- National Occupational Employment and Wage Estimates in 2021, we can find that there is huge deviation (ranging from $25000 to $370000) in yearly compensation and wages.

According to census 2020 of the United States, around 37.9% population of people age 25 and above has undergraduate degrees and 14.4 % had completed master’s degree and above including professional degree (census, 2020). This is higher than previous census. It means every year more and more people taking college degree is increasing with objective of getting higher and higher compensation during their professional life. However, it is evident from above facts that there is discrepancy between expected annual compensation and realized annual compensation. So, this gap in yearly compensation may be caused by several reasons- gender, experience, nature or types of companies and level of education. (Gender Pay Gap statistics,2022; Altonji et al. (2022); Goldsmith & Veum (2002)).

Despite being a developed nation, pay differences based on gender is still persistent in US may be at the time of hiring, performance evaluation, post hiring, among others. ([Blau & Kahn, 2017](https://journals.sagepub.com/doi/full/10.1177/0730888419868748" \l "bibr23-0730888419868748); [Brett & Stroh, 1997](https://journals.sagepub.com/doi/full/10.1177/0730888419868748#bibr24-0730888419868748); [Dreher, Lee, & Clerkin, 2011](https://journals.sagepub.com/doi/full/10.1177/0730888419868748#bibr39-0730888419868748); [Kronberg, 2013](https://journals.sagepub.com/doi/full/10.1177/0730888419868748" \l "bibr61-0730888419868748); [Petersen & Saporta, 2004](https://journals.sagepub.com/doi/full/10.1177/0730888419868748#bibr70-0730888419868748); [Quintana-García & Elvira, 2016](https://journals.sagepub.com/doi/full/10.1177/0730888419868748#bibr74-0730888419868748), [Castilla & Benard, 2010](https://journals.sagepub.com/doi/full/10.1177/0730888419868748#bibr30-0730888419868748); Harris and et al., 2019). Despite the fact that this gender discrepancy is getting slowly improved in US with the passage of time, however, it is still not satisfactory ([Goldin, 2014](https://journals.sagepub.com/doi/full/10.1177/0730888419868748#bibr49-0730888419868748)).

The number of years of experience is all about learning by doing, co-operative learning and dealing with real life situations. Hence, with increase in years of experience skill, experitise, problem solving attitude get better in an individual which helps them to enhance their annual compensation (Alsulami, 2018; Wannakrairoj, 2013; Saqib and et al., 2016). So, this is another factor which may substantially chanage one’s annual compensation.

Another factor determining compensation for an employee is the type of company he or she is working. In our research, we analyzed the difference in the compensation an employees is getting basis on the technological and non-technological company he or she is working. In US, it is a dream for an individual to work in technological company for better compensation and future prospects. However, according to the Glassdoor Job Market Report, 2018 even in tech companies only 57% job opening are related to technological roles. Hence, it is evident that even working in non-tech companies, an individual can make lucrative earnings.

Also, according to the new Dice Salary Survey we found that the number of years of experience and nature of a company (technological and non-technological) simultaneously affect the annual compensation of an employee too. According to eh new Dice Salary Survey, more years of experience in a technological company, annual compensation can increase by 9.8% within a year and almost 25% within two years of experience. It means, the more we spend in technological companies, more we can expect the substantial increase in annual compensation of an individual.

So, we realized that still discrepancy exists in the annual compensation of an employee within the United States and in other countries too. It is due to several factors; however, the most common determinants were educational level, gender, years of experience. But it is not found in any article that the discrepancy in annual compensation is due to the nature of the company too. So, in this article we tried analyzing the effect on yearly compensation basically based on the nature of the companies. More specifically, we tried taking annual compensation of employees in US cfrom Apple and Amazon companies representing tech and non-tech companies respectively. Furthermore, we considered annual compensation rather than annual salary or hourly wage. In yearly compensation, we tried incorporating basic salary, bonus, and stock grant value. Also, we tried analyzing the impact of master’s degree and undergraduate degree on an employee’s yearly compensation. Nevertheless, we also tried analyzing the effect of years of experience and gender in employee’s annual compensation motivated by the literatures above.

**Research Gap**

Going through several, we found several literatures supporting the deviation in annual compensation is due to several reasons. However, we didn’t find any literature incorporating the nature or type of a company considering specific companies in their analysis to analyze their impact on the change in yearly compensation. For this, we took two companies- Apple, representing technological company and Amazon, representing non-technological company, and tried to analyze the effect on yearly compensation of an employee based on the nature of the company.

Hence, our entire work is confined around- analyzing the impact on yearly compensation of an employee due to education, experience, gender based on the type of a company (technological company or non-technology company).

**Econometric Model and Estimation Method**

Based on the above relationship of variables we tried to construct an econometric model:

Compensation= ---------------------- (1)

|  |  |
| --- | --- |
| * Table 1 : Variable Description | |
| * Annual Compensation | * Yearly total compensation which is the sum of base salary, bonus and stock grant value |
| * Exper | * Year of experience |
| * Educ | * = 1 if Master’s Degree |
| * Gender | * = 1 if male |
| * Company | * = 1 if Amazon company |

In the model, we considered linear relationship between the variables with annual compensation. However, we also want to find whether the discrepancy in annual compensation is due to only education or also due to the nature of nature of company, so, we introduction interaction term in the model. In this model, the variable “Company” will work as a control variable to find whether the difference in annual compensation is due to innate qualities of an individual or is it due to the nature of company too. We tried to consider explanatory having least inter-relationship between themselves to avoid multicollinearity in the model. We tried putting together only those explanatory variables to avoid endogeneity, especially simultaneity issue- no variable have simultaneous relation with annual compensation.

We constructed classical or ordinary linear regression model. So, to keep up with all the assumptions in OLS model, we checked all the assumptions for robustness of the model. We

**Data Overview**

Our data was collected from the site levels fyi. Our dataset originally contained 62,642 observations and 29 variables. We removed all null and unnecessary data which were nonrelated to our analysis.Firstly, we restricted our data to locations within the US because companies like Apply has its business expansion throughout the world. Secondly, we filtered the entire data set based on two companies- Amazon and Apple. Thus, we were left with 1,421 observations and 18 variables. Thirdly, only the data related to the variables- total compensation, years of experience, gender, and education were confined in our data set.

**Results**

Summary Statistics

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Table 2: Summary Statistics | | | | | |
| Variables | N | Mean | Standard Deviation | Minimum | Maximum |
| Totalyearlycompensation | 1421 | 229681.0 | 85636.0 | 21,000 | 790,000 |
| Years of experience | 1421 | 5.150 | 4.770 | 0 | 36 |
| Years at company | 1421 | 2.110 | 2.480 | 0 | 15 |
| Basesalary | 1421 | 145,823.0 | 25,677.0 | 18,000 | 260,000 |
| Stockgrantvalue | 1421 | 65,966.0 | 67,256.0 | 0 | 630,000 |
| Bonus | 1421 | 17,921.0 | 20,633.0 | 0 | 150,000 |
| Educ | 1421 | 0.482 | 0.500 | 0 | 1 |
| Company | 1421 | 0.818 | 0.368 | 0 | 1 |
| Gender | 1421 | 0.863 | 0.344 | 0 | 1 |

Considering the model (1), we obtained the estimator as below:

|  |  |
| --- | --- |
| Table 3 OLS Results. Dependent Variable: Compensation | |
| Independent Variables | (1) |
| Educ | 26,921.000\*\*\*  (7,800.000) |
| Exper | 11,473.000\*\*\*  (356.000) |
| Gender | 8,898.000\*  (4,868.000) |
| Company | -15,931.000\*\*\*  (6,138.000) |
| Educ:Company | -29,950.000\*\*\*  (8,638.000) |
| Constant | 174,761.000\*\*\*  (7,063.000) |
| Observations | 1421 |
| R-squared | 0.468 |
| Adjusted R­-squared | 0.466 |

Note: The quantity in the parenthesis is standard deviation. ( \*p<0.1; \*\*p<0.05; \*\*\*p<0.0)

We can see that all the variables are significant to annual compensation, at least 10% level of significance. However, this model is diagnosed with heteroscedasticity. So, we considered improving this model further converting the original OLS model into weighted least square (WLS) model taking weight. Due to this, we shall be able to obtain unbiased estimators which is not possible in the case of OLS model having heteroscedasticity.

**Weighted Least Square Method**

Our initial OLS model was witnessed with heteroscedasticity while carrying out BP test and White test. So, this will lead to biased estimator. So, it is necessary to get rid of unequal variance between predicted variable and . Hence, we used weighted least square (WLS) model because WLS estimators are equivalent to the OLS estimator of the transformed model. The original model (1) in converted into WLS model taking the weight (w) as below:

**= + + + + +**

+ Educ + Gender + Company + Educ: Company + V\* ----------(2)

Using model (2) we get better estimators as heteroscedasticity is addressed in this model. After this, we regressed model (2) and obtained the output as below:

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| --- | --- | --- |
| Table 6 WLS Results. Dependent Variable: Compensation | | |
| Independent Variables | OLS Estimation (1) | WLS Estimation (2) |
| Educ | 26,921.000\*\*\*  (7,800.000) | 26,025.000\*\*\*  (7,836.000) |
| Exper | 11,473.000\*\*\*  (356.000) | 13,307.000\*\*\*  (435.000) |
| Gender | 8,898.000\*  (4,868.000) | -249.000  (3,042.000) |
| Company | -15,931.000\*\*\*  (6,138.000) | -14,860.000\*\*  (5,817.000) |
| Educ:Company | -29,950.000\*\*\*  (8,638.000) | -27,025.000\*\*\*  (8,229.000) |
| Constant | 174,761.000\*\*\*  (7,063.000) | 173,456.000\*\*\*  (6,098.000) |
| Observations | 1421 | 1421 |
| R-squared | 0.468 | 0.427 |
| Adjusted R­-squared | 0.466 | 0.425 |

Note: The quantity in parenthesis is standard deviation. (\*p<0.1; \*\*p<0.05; \*\*\*p<0.01)

We can observe that when considering OLS estimation, all the variables turned out to be significant but taking WLS estimation, except Gender variable. For instance, Educ variable is significant to annual compensation. Since, Educ is a dummy variable where under-graduate is base dummy and Eudc estimator is positive. It means, no matter what kind of company we work our education level i.e. higher education (Master’s degree) has a positive impact on annual compensation. In other words, master’s degree students will make $26025 more with the increase in level from under-graduate to graduate level. Furthermore, the number of years of experience (Exper) is positively associated with annual compensation. With every increase in years of experience, annual compensation will increase by $13,307. When we observe the estimate of company variable, it is negative. Being dummy variable where base dummy is Amazon, it indicates that Apple compensated more to its employees than Amazon. Observing the interaction term “Educ.Company” we can conclude that tech company pay more than non-tech company based on the education level. It means, the nature or type of a company matters in terms of annual compensation, given the education level.

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| --- | --- | --- |
| Table 5 Heteroscedasticity Test of OLS model | | |
|  | BP | P value |
| Breusch-Pagan Test | **0.0000001, df = 5** | 1 |
| White Test | **0.0000001, df = 2** | 1 |

**Robustness checking**

We carried several robustness checking considering the first model. Firstly, we carried multi-collinearity check using variance inflation factor (VIF) and presented both in tabulated and heat map of correlation of explanatory variables.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Table 4 Variance Inflation Factor (VIF) | | | | |
| Educ | exper | Gender | Company | Educ:Company |
| 5.51 | 1.05 | 1.02 | 2.03 | 6.45 |

A picture containing chart

Description automatically generated

We found that there is no any multi-collinearity among explanatory variables. Basically, if we find VIF <10 then it is considered the absence of multi-collinearity in the model.

Secondly, we carried heteroscedasticity test using BP test and White test.

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| --- | --- | --- |
| Table 5 Heteroscedasticity Test of OLS model | | |
|  | BP | P value |
| Breusch-Pagan Test | 176 (df = 5) | <0.0000000000000002 |
| White Test | 173 (df = 2) | <0.0000000000000002 |

We found that there exists heteroscedaticity in the model. So, we converted the original OLS model into WLS model and found the estimate.

Checking over-specification

|  |  |  |
| --- | --- | --- |
| Table 3 OLS Results. Dependent Variable: Compensation | | |
| Independent Variables | (1) | (2) |
| Educ | 26,025.000\*\*\*  (7,836.000) | 26,005.000\*\*\*  (7,830.000) |
| Exper | 13,307.000\*\*\*  (435.000) | 13,305.000\*\*\*  (434.000) |
| Gender | -249.000  (3,042.000) |  |
| Company | -14,860.000\*\*  (5,817.000) | -14,900.000\*\*  (5,795.000) |
| Educ:Company | -27,025.000\*\*\*  (8,229.000) | -26,987.000\*\*\*  (8,212.000) |
| Constant | 173,456.000\*\*\*  (6,098.000) | 173,290.000\*\*\*  (5,746.000) |
| Observations | 1421 | 1421 |
| R-squared | 0.427 | 0.427 |
| Adjusted R­-squared | 0.425 | 0.426 |

We tried to analyze over specification in the model. Since, the model consists of several explanatory variables and firstly we considered OLS and then we found estimate using WLS and found that Gender variable is insignificant. This made us doubtful about over specification in the model. So, we tried carrying WLS without Gender variable and with Gender variable and checked both R-squared and Adjsuted R-Squared. We found that there is no much chance in significance so considered that Gender variable is over specified and removed that from the model and estimated the model.

Partialling out Effect of Education

|  |  |  |
| --- | --- | --- |
| Variable | Estimate | p-value |
| Educ\_res | 26921 | 0.012 |
| Intercept | 229681 | 0.0000000000000002 |

While carrying out partialing out effect, we tried analyzing the pure effect of education on annual compensation. Surprisingly, the coefficient of Educ variables remained to be the same. It means the estimate from Educ without partialling out and after partialing out are the same. It is because there is almost no multi-collinearity between explanatory variables.

**Conclusion**

Education has a significant impact on yearly compensation for both companies. Since, education is dummy variable, so it means master’s degree has positive impact on yearly compensation on both the companies. In comparison to companies, Apple pays more to its employees based on education level than Amazon.  Years of experience too have a substantial impact on yearly compensation level.  Gender has no significant impact on yearly compensation.

References:

*2019 Glassdoor data on the gender pay gap and salary transparency*. (n.d.). Retrieved December 7, 2022, from https://about-content.glassdoor.com/app/uploads/sites/2/2019/03/Gender-Pay-Gap-Fact-Sheet-2019.pdf

Alsulami, H. (2018, January 8). *The effect of education and experience on wages: The case study of saudi arabia*. American Journal of Industrial and Business Management. Retrieved December 6, 2022, from https://www.scirp.org/journal/paperinformation.aspx?paperid=81882

American Psychological Association. (n.d.). *Apa PsycNet*. American Psychological Association. Retrieved December 6, 2022, from https://psycnet.apa.org/record/1997-06155-001

*Do female and ethnically diverse executives endure inequity in ... - JSTOR*. (n.d.). Retrieved December 7, 2022, from https://www.jstor.org/stable/43897829

Freund KM;Raj A;Kaplan SE;Terrin N;Breeze JL;Urech TH;Carr PL; (n.d.). *Inequities in academic compensation by gender: A follow-up to the National Faculty Survey Cohort Study*. Academic medicine : journal of the Association of American Medical Colleges. Retrieved December 6, 2022, from https://pubmed.ncbi.nlm.nih.gov/27276007/

*The gender wage gap: Extent, trends, and explanations*. IZA. (n.d.). Retrieved December 6, 2022, from https://www.iza.org/publications/dp/9656/the-gender-wage-gap-extent-trends-and-explanations#:~:text=Francine%20D.%20Blau%2C%20Lawrence%20M.%20Kahn%20published%20in%3A,wage%20gap%2C%20which%20declined%20considerably%20over%20this%20period.

*A grand gender convergence: Its last Chapter - Harvard University*. (n.d.). Retrieved December 7, 2022, from https://scholar.harvard.edu/files/goldin/files/goldin\_aeapress\_2014\_1.pdf

Harris, O., Karl, J., & Lawrence, E. R. (1970, January 1). *CEO compensation and earnings management: Does gender really matters?: Semantic scholar*. undefined. Retrieved December 6, 2022, from https://www.semanticscholar.org/paper/CEO-compensation-and-earnings-management%3A-Does-Harris-Karl/08f7d7194cd9d553803c8bd0ce95304b88de3dc9

*Human capital - Harvard University*. (n.d.). Retrieved December 7, 2022, from https://scholar.harvard.edu/files/goldin/files/human\_capital\_handbook\_of\_cliometrics\_0.pdf

*Job Avenues and the race earnings gap.* (n.d.). Retrieved December 7, 2022, from https://www.atlantafed.org/-/media/Documents/news/conferences/2013/caed/D3Kronberg.pdf

*The paradox of meritocracy in organizations - sage journals*. (n.d.). Retrieved December 7, 2022, from https://journals.sagepub.com/doi/abs/10.2189/asqu.2010.55.4.543

Petersen, T., Saporta, I., & Seidel, M. (1970, January 1). *[PDF] getting hired: Race and sex differences: Semantic scholar*. undefined. Retrieved December 6, 2022, from https://www.semanticscholar.org/paper/Getting-Hired%3A-Race-and-Sex-Differences-Petersen-Saporta/a4d21ad4638f8c0a1c25fb4ec61fd69e99af235a

Wit Wannakrairoj - Institute for Manufacturing (IFM). (n.d.). Retrieved December 6, 2022, from https://www.ifm.eng.cam.ac.uk/people/ww313/