Final Project: Analysis on STEM Position Salaries

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1.1 Introduction

Many International students leave their countries to pursue careers in a STEM-related field, including positions like software engineers, business analysts, and data scientists. There's no current research paper on what influences the salary of STEM-related positions, yet there are some news articles that have performed analysis on the salary for STEM-related positions. The articles focus on comparing the salary difference between each year, providing a general overview of the industry but not insights for individual companies.

In this analysis, we want to understand what possible factors that might influence the total yearly compensation for STEM-related positions. The analysis is split into two parts. In the first part, we aim to analyze whether companies have different standards for salary across the same position. In addition, we want to examine whether the location has an impact on the compensation. A hierarchical model will be used to evaluate the variances across different companies and countries. In the second part, we want to see if other demographic features will have an impact on the compensation. This analysis fits two different hierarchical models to compare whether taking account of personal background explains the salary more than the candidate's working experience.

1.2 Summary

The analysis examines how different factors might influence the total yearly compensation and specifically focuses on how the salaries vary from location and company. Our model indicates that around 71% of the variation in total compensation can be explained by countries and companies. The analysis of the model showed that the salaries are different from countries by title and different from companies. The model indicates interesting interactions like title and experience. In addition, both years of experience and years at the company increase the salary slightly regardless of location and title.

1.3 Data

This dataset comes from Kaggle where the author scraped the CSV file from level.fyi, which is an online platform where users can report their salaries in US dollars. In this analysis, there are two possible columns for the response variable, one of them is total yearly compensation. The other option is the base salary variable. However, after examining the data, there are a lot of 0's filled in and it's counter-intuitive. The total yearly compensation data is more consistent and is one of the mandatory columns. Since the distribution of the total yearly compensation is skewed, a log transformation is used for modeling. The distribution after log transformation resembles the normal distribution and we proceed with log-transformed salary.

In addition to salaries, there are variables that we can use as predictors. This includes company, level, job title, office location, years of experience and years at the company. The office location is aggregated into a single column. To process the data, we have to split the data into city, state, and country. The data consists of users around the globe, and some countries have less than 10 data points. Since we're interested in examining the variance across different countries, we will filter out countries with less than 10 data points. In addition, we're interested in the variance across different companies, so we will filter out companies with less than 100 data points. This reduces our data to 45 thousand entries.

Some columns are optional personal information, including gender, education level. The user is not required to fill in this information when reporting their salary. Out of the 65 thousand entries, only 14 thousand have complete personal information. Therefore the research will be split into two parts. In the first part, we will focus on all of the data without using personal information. In the second part, we will add personal information and compare the two models.

1.4 EDA

In order to answer our research questions, we examine the relationship between the company and salary distribution. We see a clear difference in the total compensation in different companies. We also checked the relationship between salary and countries. The distribution of the salary varies across different countries.

For the non-hierarchical terms, including title, years-at-company, and years-of-experience, we are also interested in the interaction terms between them. The slopes of years at the company versus salary are obviously different across titles. While the slopes of years of experience versus salary are only slightly different across titles. We will pass both interaction terms to the stepwise model selection process and determine whether we should include them in our final model.

For hierarchical terms, we first examine the company-wise effects. The slope of years of experience versus salary in each company is almost the same. Therefore, we will not consider using varying slopes for years of experience variables. The slope of years at a company versus salary in each company is different, and thus we will consider doing a varying slopes model for this predictor. Most of the companies have similar trends in the relationship between salary versus title. In addition, not all of the companies have all the titles. We will consider using varying intercepts instead of varying slopes. (Appendix 1.a)

Last, we examine the country-wise effect. We sample 16 countries from countries that have more than 10 data points. The slope of years of experience versus salary in each country is different. We will consider using varying slopes for years of experience by different countries. The slope of years at a company versus salary in each company is also different, and thus we will consider doing a varying slopes model for this predictor on country. All the countries have different trends of the relationship between salary versus title. Therefore, we will consider using varying slope models on country. (Appendix 1.b)

1.5 Model Selection

In the first part of the project, we focus on the variables with no missing data at all. A stepwise model selection is used for selecting the fixed terms. Forward direction selection returns the same result as using both directions, while the backward selection returns the null model. Then we use the ANOVA test to compare against the AIC and BIC models. The p-value for the AIC model is significant. Before proceeding to add the hierarchical terms, we did a model assessment on the fixed terms linear regression model. Since the AIC model includes all the interaction terms, including the three-way interaction between title, years-of-experience and years-at-company, it makes the multicollinearity score higher than 8. We take out the three-way interaction and the interaction between years-of-experience and years-at-company to avoid high multicollinearity. Our fixed terms that will be included in the final model will be years-of-experience, title, years-at-company, the interaction between years-of-experience and title, and the interaction between years-at-company and title.

Then we proceed with the hierarchical model. We fit several different hierarchical models with the same fixed terms. This includes varying intercept with countries, varying intercept with companies, and varying intercept with both companies and countries. In order to evaluate the models, we compare their AIC values. We also try to compare the varying slopes for companies and countries. However, a lot of companies don't have sufficient data points for each title, making the model fail to converge. Therefore, we can only focus on comparing the varying intercept models with the varying slope model using title and countries. The model using the combination of varying intercept with companies and varying slope with title and countries has the smallest AIC value, and we will use this as our final model. Our final model will be:

$$
\begin{aligned}
log(salary_i) = \beta_0 + \gamma_{0,company_j} + (\beta_1 + \gamma_{1,country_j})\text{title}_{ij} \\
+ \beta_2 \text{experience}_i + \beta_3 \text{companyExp}_i + \beta_4 \text{experience}_i : \text{title}_i \\
+ \beta_5 \text{companyExp}_i : \text{title}_i + \epsilon_{ij}
\end{aligned} \tag{1}
$$

where $\epsilon_{ij} \sim N(0, \sigma^2), \gamma_{0,company} \sim N(0, \tau_0^2), \gamma_{1,country} \sim N(0, \tau_1^2)$.

For the second part of the project, we focus on the complete set of data, which reduces the number of observations to 14 thousand entries. The final model from the previous section is used to perform another stepwise model selection in both directions with three extra variables: gender, education and race. We examined the VIF score and removed two interaction terms with high VIF scores from the AIC model. Our model for the second part will be:

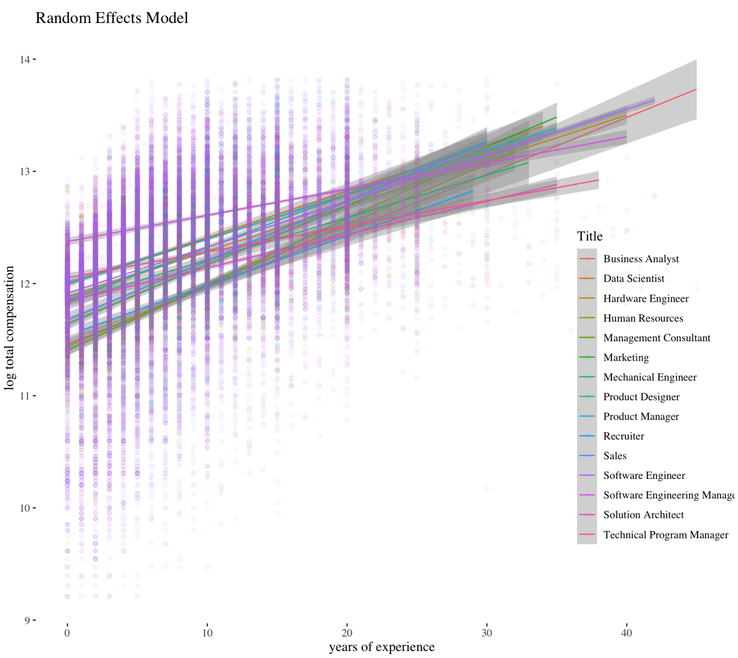
$$
\begin{aligned}
log(salary_i) = \beta_0 + \gamma_{0,company_j} + (\beta_1 + \gamma_{1,country_j})\text{title}_{ij} \\
+ \beta_2 \text{experience}_i + \beta_3 \text{companyExp}_i + \beta_4 \text{experience}_i : \text{title}_i \\
+ \beta_5 \text{companyExp}_i : \text{title}_i + \beta_6 \text{education}_i + \beta_7 \text{race}_i + \beta_8 \text{gender}_i \\
+ \beta_9 \text{education}_i : \text{race}_i + \beta_{10} \text{education}_i : \text{gender}_i \\
+ \beta_{11} \text{race}_i : \text{gender}_i + \beta_{12} \text{companyExp}_i : \text{gender}_i + \epsilon_{ij}
\end{aligned} \tag{2}
$$

1.6 Model Assessment

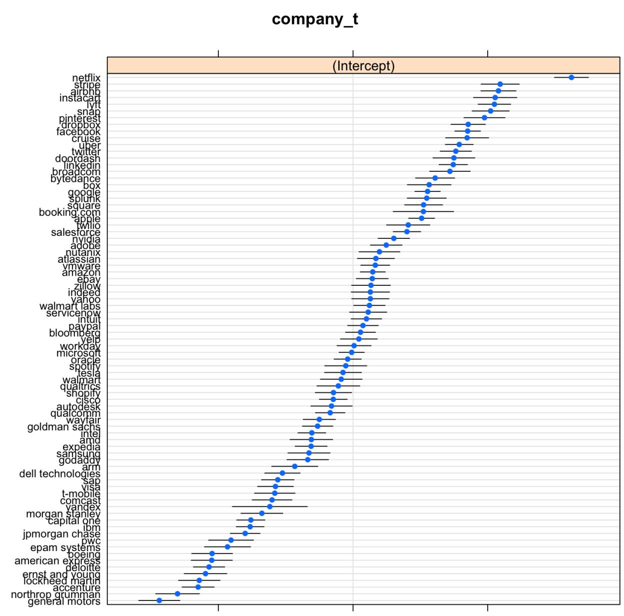
We checked the cook's distance before adding the hierarchical terms. All the cook's distances are within 0.05. The multicollinearity issue is resolved by removing the interaction terms. There are two continuous predictors in our model, years-at-company and years-of-experience. The linearity assumption is met since there's no obvious pattern in the residual versus continuous predictor plot(Appendix 1.e and 1.f). The independence and constant variance assumptions are met since there's no obvious pattern in the residual plot(Appendix 1.d). For the normality assumption, even though most of the points fall on the 45-degree line in the QQplot, there are some points on the tails that are deviating from the line(Appendix 1.c). However, there isn't much room for improvement as the response variable has already been log-transformed.

1.7 Model Result

Since we're using a combination of a random intercept and random slope model, we expect to see different intercepts and slopes across the titles. We use the years-of-experience versus log total compensation graph to visualize the slopes (Figure 1). Software engineers have the largest intercept. The slopes are also different from each title. We also visualize the random effects on intercepts by each company using dotplot (Figure 2). The coefficients from the model are shown in the table (Appendix 2).



(a) Figure 1: Random Slope Model using Title



(b) Figure 2: Random Effect of Company

Our baseline model is the total yearly compensation for business analysts around the globe, with 0 experience and 0 years at their company. Most of the titles are significant, including Software engineer manager, data scientist, and recruiter. In order to interpret our results, we select some countries and titles as examples. For the fixed effect, with all the conditions held baseline, changing the title from business analyst to software engineer manager is expected to increase the compensation by a multiplicative effect of 2.34. On the contrary, with all the conditions held at baseline, changing the title from a business analyst to a recruiter is expected to decrease the compensation by a multiplicative effect of 0.8. If the recruiter has one year of experience at the company, the compensation is expected to decrease by a multiplicative effect of 0.82. If the recruiter has one year of experience outside the company, the compensation is expected to decrease by a multiplicative effect of 0.8.

As for the random effects of companies, Netflix has the most positive intercept. If the candidate works in Netflix, it increases their baseline salary by a multiplicative effect of 2.03. On the contrary, General Motors has the most negative intercept. If the candidate works in General Motors, it decreases their baseline salary by a multiplicative effect of 0.53.

As for the random effects of the countries, the United States has the most positive intercept. If the candidate works in the States, it increases their baseline salary by a multiplicative effect of 2.07. If the candidate is a software engineer manager working in the United States, their salary is expected to increase by 2.12 compared to the baseline salary in the States. On the contrary, Mexico has the most negative intercept. If the candidate works in Mexico, it decreases their baseline salary by a multiplicative effect of 0.38. If the candidate is a software engineer manager working in Mexico, their salary is expected to increase by 2.61 compared to the baseline salary in Mexico.

For the second part of the analysis, we add in gender, education, and race for the 14 thousand complete data. The coefficients from the model are shown in the table (Appendix 3). The baseline is the total yearly compensation for business analysts around the globe, female, Asian, who had their Bachelor's Degree, with 0 experience and 0 years at their company. Most titles remain significant. In addition, male, being white, education level of master degree and Ph.D. are also significant predictors. Given other conditions held baseline, if the candidate is male, their salary is expected to increase by 7%. If the candidate is white, their salary is expected to increase by 4%. For the education levels, given other conditions held baseline, if the candidate's highest education is Master's, their salary is expected to increase by 11%. If the candidate has a Ph.D. degree, their salary is expected to increase by 29%.

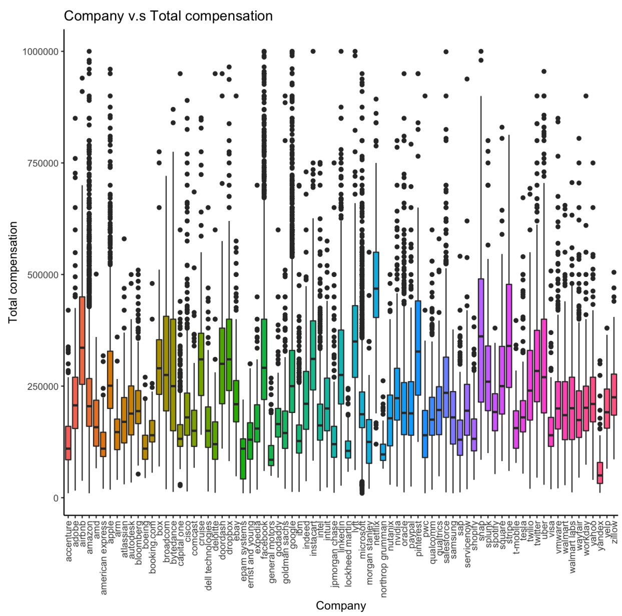
1.8 Conclusion

Overall, the hierarchical model provides insights into heterogeneity in the compensation of by country and company. Most of the variance in the dataset is explained with this hierarchical model, as the residual variance is only 0.29. The response variable is not only influenced by predictors that represent the working experience of the candidate but also shows discrepancy across different location groups and companies. After adding in personal background information, the model improved by having a smaller AIC and less residual variance. This means adding in personal information does help explain the salary better.

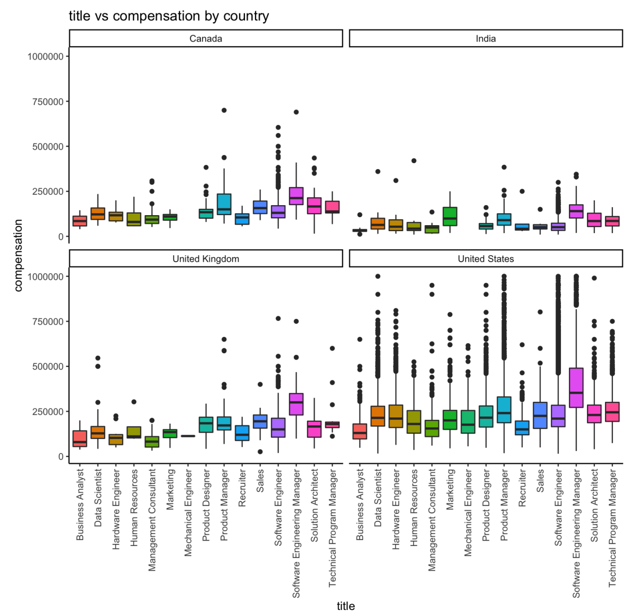
However, there are several limitations in this analysis. The normality assumption of the hierarchical linear regression model is not met. The data is imbalanced as most of the data come from the United States and software engineers. These limitations are probably due to the fact that we are using unverified data inputs from internet users. In all, the hierarchical model does help us study country-wise and company-wise random effects on the compensation and can be used for future studies on the same topic.

Appendix

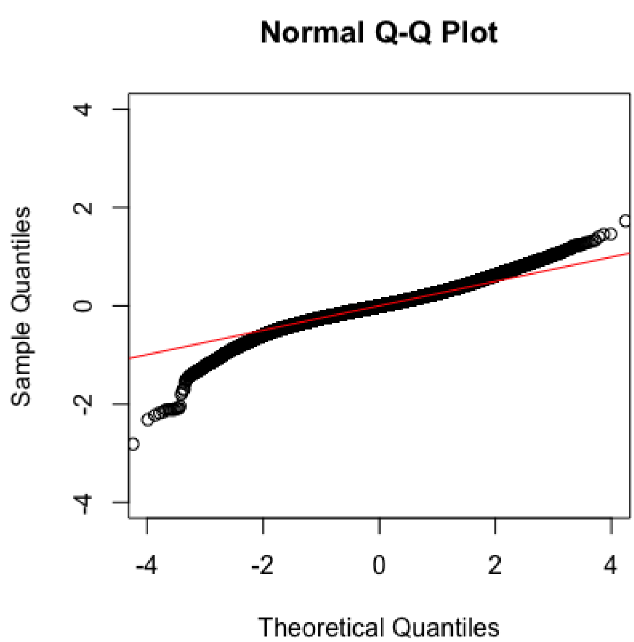
Appendix 1: Plots



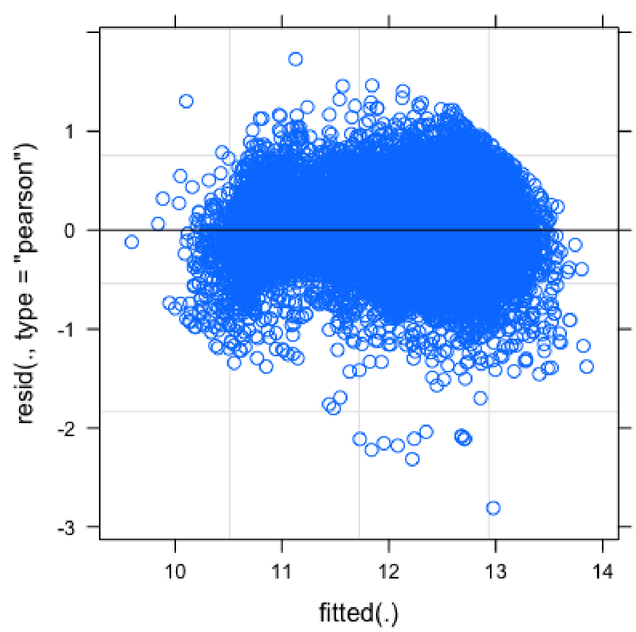
(a) Figure 1a: Company v.s Salary



(b) Figure 1b: Title v.s Salary by Country

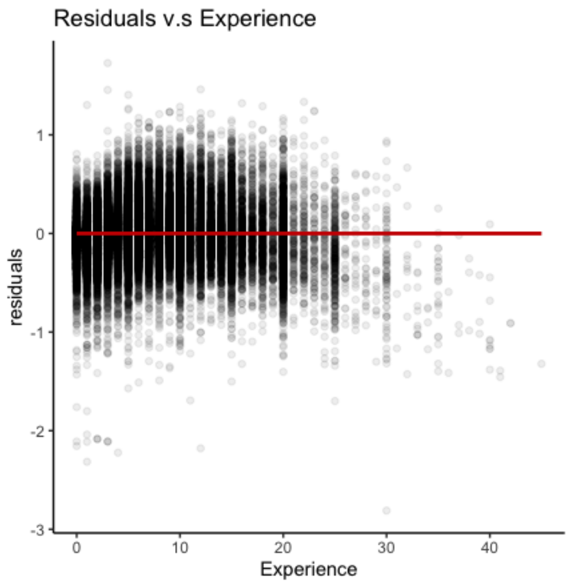


(c) Figure 1c: Normality Assumption

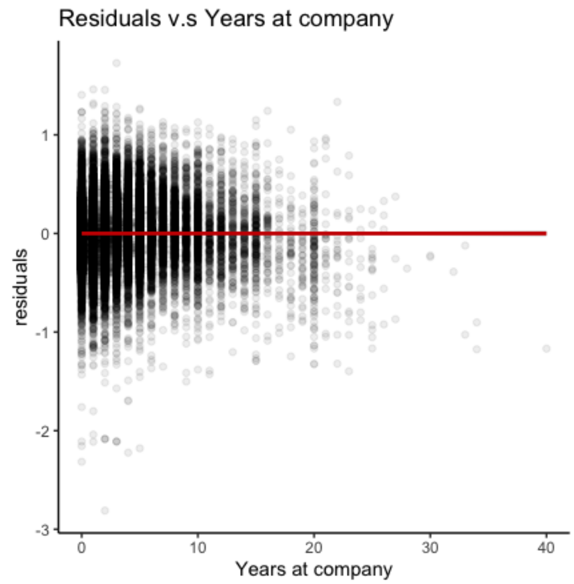


(d) Figure 1d: Independence Assumption

Appendix 1: Plots



(a) Figure 1.e: Linearity for Experience



(b) Figure 1.f: Linearity for Years at Company

Appendix 2: Model Outcome for First Model

	logtotalcomp		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	10.85	10.66 – 11.04	**<0.001**
yearsofexperience	0.05	0.04 – 0.05	**<0.001**
title [Data Scientist]	0.41	0.30 – 0.52	**<0.001**
title [Hardware Engineer]	0.38	0.30 – 0.45	**<0.001**
title [Human Resources]	-0.22	-0.37 – -0.06	**0.006**
title [Management Consultant]	0.46	0.24 – 0.68	**<0.001**
title [Marketing]	0.06	-0.19 – 0.31	0.661
title [Mechanical Engineer]	0.44	0.30 – 0.58	**<0.001**
title [Product Designer]	0.33	0.17 – 0.49	**<0.001**
title [Product Manager]	0.44	0.35 – 0.53	**<0.001**
title [Recruiter]	-0.22	-0.34 – -0.10	**<0.001**
title [Sales]	0.21	0.10 – 0.31	**<0.001**
title [Software Engineer]	0.31	0.24 – 0.39	**<0.001**
title [Software Engineering Manager]	0.85	0.72 – 0.97	**<0.001**
title [Solution Architect]	0.46	0.38 – 0.54	**<0.001**
title [Technical Program Manager]	0.46	0.37 – 0.56	**<0.001**
yearsatcompany	0.00	-0.01 – 0.01	0.566
yearsofexperience * title [Data Scientist]	-0.01	-0.01 – 0.00	0.124
yearsofexperience * title [Hardware Engineer]	-0.01	-0.02 – -0.00	**0.010**
yearsofexperience * title [Human Resources]	0.00	-0.01 – 0.01	0.428
yearsofexperience * title [Management Consultant]	-0.00	-0.01 – 0.01	0.695
yearsofexperience * title [Marketing]	0.01	0.00 – 0.02	**0.008**
yearsofexperience * title [Mechanical Engineer]	-0.02	-0.03 – -0.01	**<0.001**
yearsofexperience * title [Product Designer]	-0.01	-0.01 – 0.00	0.105
yearsofexperience * title [Product Manager]	-0.00	-0.01 – 0.00	0.311
yearsofexperience * title [Recruiter]	-0.00	-0.01 – 0.01	0.722
yearsofexperience * title [Sales]	0.00	-0.01 – 0.01	0.515
yearsofexperience * title [Software Engineer]	-0.01	-0.01 – 0.00	0.056
yearsofexperience * title [Software Engineering Manager]	-0.02	-0.03 – -0.01	**<0.001**
yearsofexperience * title [Solution Architect]	-0.02	-0.02 – -0.01	**<0.001**
yearsofexperience * title [Technical Program Manager]	-0.02	-0.02 – -0.01	**<0.001**
title [Data Scientist] * yearsatcompany	0.01	0.00 – 0.03	**0.022**
title [Hardware Engineer] * yearsatcompany	0.01	-0.00 – 0.02	0.150
title [Product Designer] * yearsatcompany	0.02	0.01 – 0.04	**<0.001**
title [Product Manager] * yearsatcompany	-0.00	-0.01 – 0.01	0.884
title [Recruiter] * yearsatcompany	0.03	0.01 – 0.05	**0.001**
title [Sales] * yearsatcompany	0.02	0.01 – 0.04	**0.003**
title [Software Engineer] * yearsatcompany	0.00	-0.01 – 0.01	0.545
title [Software Engineering Manager] * yearsatcompany	-0.00	-0.01 – 0.01	0.471
title [Solution Architect] * yearsatcompany	0.01	-0.01 – 0.02	0.337
title [Technical Program Manager] * yearsatcompany	0.01	-0.01 – 0.02	0.318
Random Effects			
σ^2	0.08		
τ_{00} company_t	0.11		
τ_{00} country	0.22		
τ_{11} country.titleData Scientist	0.04		
τ_{11} country.titleHardware Engineer	0.02		
τ_{11} country.titleHuman Resources	0.08		
τ_{11} country.titleManagement Consultant	0.27		
τ_{11} country.titleMarketing	0.32		
τ_{11} country.titleMechanical Engineer	0.09		
τ_{11} country.titleProduct Designer	0.14		
τ_{11} country.titleProduct Manager	0.03		
τ_{11} country.titleRecruiter	0.03		
τ_{11} country.titleSales	0.04		
τ_{11} country.titleSoftware Engineer	0.02		
τ_{11} country.titleSoftware Engineering Manager	0.07		
τ_{11} country.titleSolution Architect	0.02		
τ_{11} country.titleTechnical Program Manager	0.04		
ρ_{01} country.titleData Scientist	-0.69		
ρ_{01} country.titleHardware Engineer	-0.69		
ρ_{01} country.titleHuman Resources	-0.55		
ρ_{01} country.titleManagement Consultant	-0.30		
ρ_{01} country.titleMarketing	0.27		
ρ_{01} country.titleMechanical Engineer	-0.78		
ρ_{01} country.titleProduct Designer	-0.54		
ρ_{01} country.titleProduct Manager	-0.70		
ρ_{01} country.titleRecruiter	-0.35		
ρ_{01} country.titleSales	-0.42		
ρ_{01} country.titleSoftware Engineer	-0.54		
ρ_{01} country.titleSoftware Engineering Manager	-0.61		
ρ_{01} country.titleSolution Architect	-0.85		
ρ_{01} country.titleTechnical Program Manager	-0.78		
N company_t	79		
N country	31		
Observations	45455		
Marginal R^2 / Conditional R^2	0.492 / NA		

Appendix 3: Model Outcome for Second Model

	logtotalcomp		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	10.79	10.57 – 11.02	**<0.001**
yearsofexperience	0.04	0.03 – 0.05	**<0.001**
Education [Highschool]	0.07	-0.18 – 0.31	0.593
Education [Master's Degree]	0.10	0.08 – 0.13	**<0.001**
Education [PhD]	0.26	0.19 – 0.32	**<0.001**
Education [Some College]	-0.09	-0.25 – 0.08	0.318
title [Data Scientist]	0.36	0.21 – 0.51	**<0.001**
title [Hardware Engineer]	0.37	0.27 – 0.47	**<0.001**
title [Human Resources]	-0.09	-0.46 – 0.28	0.642
title [Management Consultant]	0.44	0.31 – 0.57	**<0.001**
title [Marketing]	0.11	-0.14 – 0.37	0.386
title [Mechanical Engineer]	0.50	0.33 – 0.66	**<0.001**
title [Product Designer]	0.35	0.09 – 0.61	**0.008**
title [Product Manager]	0.54	0.39 – 0.68	**<0.001**
title [Recruiter]	-0.18	-0.33 – -0.03	**0.018**
title [Sales]	0.18	-0.02 – 0.38	0.071
title [Software Engineer]	0.34	0.23 – 0.46	**<0.001**
title [Software Engineering Manager]	0.89	0.74 – 1.04	**<0.001**
title [Solution Architect]	0.49	0.36 – 0.62	**<0.001**
title [Technical Program Manager]	0.45	0.31 – 0.59	**<0.001**
Race [Black]	-0.03	-0.09 – 0.03	0.290
Race [Hispanic]	-0.02	-0.08 – 0.04	0.481
Race [Two Or More]	0.06	-0.00 – 0.12	0.051
Race [White]	0.04	0.01 – 0.07	**0.005**
yearsatcompany	0.00	-0.01 – 0.01	0.996
gender [Male]	0.07	0.05 – 0.09	**<0.001**
gender [Other]	0.06	-0.19 – 0.30	0.653
Education [Highschool] * Race [Black]	-0.06	-0.31 – 0.20	0.672
Education [Master's Degree] * Race [Black]	-0.01	-0.06 – 0.05	0.821
Education [PhD] * Race [Black]	-0.13	-0.30 – 0.05	0.157
Education [Some College] * Race [Black]	-0.07	-0.26 – 0.12	0.477
Education [Highschool] * Race [Hispanic]	0.06	-0.12 – 0.24	0.528
Education [Master's Degree] * Race [Hispanic]	0.01	-0.04 – 0.06	0.745
Education [PhD] * Race [Hispanic]	-0.10	-0.20 – 0.01	0.067
Education [Some College] * Race [Hispanic]	-0.02	-0.21 – 0.17	0.857
Education [Highschool] * Race [Two Or More]	-0.04	-0.26 – 0.19	0.762
Education [Master's Degree] * Race [Two Or More]	-0.00	-0.06 – 0.05	0.915
Education [PhD] * Race [Two Or More]	-0.03	-0.16 – 0.10	0.667
Education [Some College] * Race [Two Or More]	-0.06	-0.27 – 0.14	0.555
Education [Highschool] * Race [White]	-0.09	-0.23 – 0.04	0.180
Education [Master's Degree] * Race [White]	-0.03	-0.05 – -0.00	**0.027**
Education [PhD] * Race [White]	-0.07	-0.12 – -0.02	**0.003**
Education [Some College] * Race [White]	-0.01	-0.14 – 0.12	0.887
yearsofexperience * title [Data Scientist]	-0.00	-0.01 – 0.01	0.787
yearsofexperience * title [Hardware Engineer]	-0.00	-0.01 – 0.01	0.573
yearsofexperience * title [Human Resources]	0.00	-0.01 – 0.02	0.607
yearsofexperience * title [Management Consultant]	0.00	-0.01 – 0.01	0.805
yearsofexperience * title [Marketing]	0.02	0.00 – 0.03	**0.010**
yearsofexperience * title [Mechanical Engineer]	-0.01	-0.02 – 0.01	0.431
yearsofexperience * title [Product Designer]	0.00	-0.01 – 0.01	0.961
yearsofexperience * title [Product Manager]	-0.00	-0.01 – 0.01	0.817
yearsofexperience * title [Recruiter]	0.00	-0.01 – 0.02	0.675
yearsofexperience * title [Sales]	0.02	0.01 – 0.03	**0.006**
yearsofexperience * title [Software Engineer]	-0.00	-0.01 – 0.01	0.527
yearsofexperience * title [Software Engineering Manager]	-0.01	-0.02 – -0.00	**0.018**
yearsofexperience * title [Solution Architect]	-0.01	-0.02 – 0.00	0.250
yearsofexperience * title [Technical Program Manager]	-0.01	-0.02 – -0.00	**0.010**
title [Data Scientist] * yearsatcompany	0.01	-0.01 – 0.03	0.240
title [Hardware Engineer] * yearsatcompany	0.00	-0.01 – 0.02	0.889
title [Human Resources] * yearsatcompany	0.01	-0.01 – 0.03	0.286
title [Management Consultant] * yearsatcompany	0.03	0.01 – 0.04	**0.004**
title [Marketing] * yearsatcompany	-0.01	-0.03 – 0.01	0.325
title [Mechanical Engineer] * yearsatcompany	0.01	-0.02 – 0.03	0.579
title [Product Designer] * yearsatcompany	0.01	-0.01 – 0.03	0.169
title [Product Manager] * yearsatcompany	-0.00	-0.02 – 0.01	0.537

Appendix 3: Model Outcome for Second Model, Continued

title [Recruiter] * yearsatcompany	0.05	0.02 – 0.07	**0.001**
title [Sales] * yearsatcompany	-0.00	-0.02 – 0.02	0.737
title [Software Engineer] * yearsatcompany	-0.00	-0.02 – 0.01	0.716
title [Software Engineering Manager] * yearsatcompany	-0.01	-0.02 – 0.00	0.115
title [Solution Architect] * yearsatcompany	0.00	-0.01 – 0.02	0.879
title [Technical Program Manager] * yearsatcompany	0.00	-0.01 – 0.02	0.737
Education [Highschool] * gender [Male]	-0.06	-0.28 – 0.16	0.564
Education [Master's Degree] * gender [Male]	-0.04	-0.06 – -0.01	**0.005**
Education [PhD] * gender [Male]	0.04	-0.03 – 0.10	0.269
Education [Some College] * gender [Male]	0.01	-0.11 – 0.13	0.866
Education [Highschool] * gender [Other]	-0.50	-0.88 – -0.13	**0.008**
Education [Master's Degree] * gender [Other]	0.14	-0.03 – 0.31	0.118
Education [PhD] * gender [Other]	-0.00	-0.36 – 0.36	0.990
Education [Some College] * gender [Other]	-0.11	-0.55 – 0.33	0.626
Race [Black] * gender [Male]	-0.02	-0.08 – 0.05	0.614
Race [Hispanic] * gender [Male]	-0.03	-0.09 – 0.03	0.370
Race [Two Or More] * gender [Male]	-0.07	-0.13 – -0.00	**0.047**
Race [White] * gender [Male]	-0.04	-0.07 – -0.01	**0.004**
Race [Black] * gender [Other]	0.09	-0.39 – 0.56	0.722
Race [Hispanic] * gender [Other]	0.19	-0.17 – 0.56	0.297
Race [Two Or More] * gender [Other]	-0.13	-0.38 – 0.11	0.286
Race [White] * gender [Other]	-0.15	-0.40 – 0.09	0.214
yearsatcompany * gender [Male]	0.01	0.00 – 0.01	**<0.001**
yearsatcompany * gender [Other]	0.05	0.02 – 0.08	**0.001**

Random Effects	
σ^2	0.08
$\tau_{00\ \text{company\_t}}$	0.11
$\tau_{00\ \text{country}}$	0.23
$\tau_{11\ \text{country.titleData Scientist}}$	0.08
$\tau_{11\ \text{country.titleHardware Engineer}}$	0.02
$\tau_{11\ \text{country.titleHuman Resources}}$	0.39
$\tau_{11\ \text{country.titleManagement Consultant}}$	0.03
$\tau_{11\ \text{country.titleMarketing}}$	0.25
$\tau_{11\ \text{country.titleMechanical Engineer}}$	0.08
$\tau_{11\ \text{country.titleProduct Designer}}$	0.26
$\tau_{11\ \text{country.titleProduct Manager}}$	0.06
$\tau_{11\ \text{country.titleRecruiter}}$	0.04
$\tau_{11\ \text{country.titleSales}}$	0.11
$\tau_{11\ \text{country.titleSoftware Engineer}}$	0.03
$\tau_{11\ \text{country.titleSoftware Engineering Manager}}$	0.06
$\tau_{11\ \text{country.titleSolution Architect}}$	0.04
$\tau_{11\ \text{country.titleTechnical Program Manager}}$	0.05
$\rho_{01\ \text{country.titleData Scientist}}$	-0.72
$\rho_{01\ \text{country.titleHardware Engineer}}$	-0.84
$\rho_{01\ \text{country.titleHuman Resources}}$	-0.66
$\rho_{01\ \text{country.titleManagement Consultant}}$	-0.38
$\rho_{01\ \text{country.titleMarketing}}$	0.06
$\rho_{01\ \text{country.titleMechanical Engineer}}$	-0.93
$\rho_{01\ \text{country.titleProduct Designer}}$	-0.57
$\rho_{01\ \text{country.titleProduct Manager}}$	-0.78
$\rho_{01\ \text{country.titleRecruiter}}$	-0.65
$\rho_{01\ \text{country.titleSales}}$	-0.43
$\rho_{01\ \text{country.titleSoftware Engineer}}$	-0.63
$\rho_{01\ \text{country.titleSoftware Engineering Manager}}$	-0.80
$\rho_{01\ \text{country.titleSolution Architect}}$	-0.90
$\rho_{01\ \text{country.titleTechnical Program Manager}}$	-0.75
$N_{\text{company\_t}}$	79
N_{country}	24
Observations	14756
Marginal R^2 / Conditional R^2	0.528 / NA