Capstone Report
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I. Executive Summary

In today's rapidly evolving business landscape, understanding the impact of CEO backgrounds on organizational dynamics is crucial for maintaining competitiveness and driving performance excellence. This study delves into the influence of CEO prior work experience on internal labor markets and turnover rates within professional services firms, focusing on Deloitte and Ernst & Young (EY) as case studies. The motivation behind this analysis stems from the shifting backgrounds of CEOs in the accounting profession, particularly their transition from auditing to consulting roles as firms like the Big 4 expand their consulting divisions. This transition potentially shapes employee allocation strategies, influencing promotions, departures, and other aspects of organizational operations.

Using employment history data from individuals previously employed by Deloitte and EY, encompassing job experiences and roles within the organizations, along with CEO data dating back to 1994, the analysis explores the relationship between CEO backgrounds and employee dynamics. Data cleaning and preprocessing measures were undertaken to ensure data integrity, including the classification of job records into auditing, consulting, or other categories based on occupation codes, and refinement of data types for subsequent analysis.

The methodology involves the classification of job records, examination of job changes such as exits (departures from the firm), lateral movements, promotions, and demotions within the firms, and regression analysis to assess the significance of CEO background alignment on employee transitions. The 'shared focus' variable was a pivotal indicator of alignment in the regression analysis between CEOs and employees in either auditing or consulting within these firms. Results from regression models reveal notable variations between Deloitte and EY. Deloitte exhibits statistical significance across multiple dependent variables, indicating a correlation between CEO 'shared focus' and the probability of lateral movements, promotions, demotions, and lateral movements within the organization. Conversely, EY's results show significance primarily in the promotion variable, suggesting a correlation between CEO 'shared focus' and the likelihood of promotions within the firm.

These findings have significant implications for professional services firms, offering insights into the dynamics of employee movements, resource allocation strategies, and turnover costs. By understanding how CEO backgrounds influence organizational operations, firms can optimize workforce allocation, tailor retention efforts, and align strategic priorities effectively. Practical implications include guidance for HR and executive leadership teams to navigate recruitment challenges, enhance retention strategies, and foster a culture of employee engagement.

Moving forward, several avenues could be explored to deepen the understanding and inform evidence-based strategies for enhancing organizational effectiveness. This includes broadening the analysis to encompass a broader spectrum of accounting firms and integrating qualitative research methods to gain deeper insights into subjective experiences driving workforce allocation strategies and retention efforts. In conclusion, this study contributes to a deeper understanding of managerial influences within professional services firms. By unraveling the intricate relationship between CEO backgrounds and organizational outcomes, this research informs strategic decision-making processes and helps firms stay competitive in a dynamic business environment.

II. Introduction/Background

A. Context

In today's changing world, companies like accounting firms are doing more than just number-crunching. Take the Big 4 firms, for example. They are not just focused on auditing; they have expanded into consulting too. Who's leading these firms? CEOs, who often have a background in one of these areas—either auditing or consulting. So, what does this mean for the rest of the company? The goal of this analysis is to investigate whether the prior work experience of CEOs at Deloitte and Ernst & Young (EY) distorts internal labor markets and/or creates higher turnover costs in non-related segments.

B. Motivation

The accounting profession faces challenges in hiring new auditors. This can be attributed to generational shifts, diminished excitement surrounding the job tasks, and comparatively lower wages. An underexplored explanation revolves around the evolving backgrounds of CEOs leading accounting firms, transitioning from auditing to consulting roles as the Big 4 firms expand their consulting divisions. This shift in CEO experience potentially shapes employee allocation strategies concerning promotions, departures, and other aspects. Given the CEO's prior work experience, does it determine their emphasis on specific areas within the firm? In simpler terms, does a CEO's previous tenure in the consulting arm correlate with reduced resource allocation towards auditing, possibly hindering recruitment efforts or providing lesser incentives for employee retention, consequently leading to increased turnover? This study aims to examine whether a CEO's background influences organizational operations and if it contributes to heightened turnover rates in certain segments of the business.

C. Importance

Understanding the impact of CEOs' prior work experience can affect the organizational dynamics within firms and this is crucial for a few reasons. Firstly, it sheds light on the mechanisms in place to understand workforce allocation and resource distribution. These are both fundamental aspects of organizational efficiency and effectiveness. By uncovering preferences stemming from CEO backgrounds, firms can ensure treatment of different business segments is equal. Secondly, the study investigates a pressing issue in the accounting profession: the challenge of hiring and retaining talent, particularly in auditing roles. This analysis can identify if there are factors contributing to higher turnover costs in non-related segments; which offers valuable insights for firms grappling with recruitment difficulties and seeking to enhance employee retention strategies. Moreover, as accounting firms evolve, understanding how CEO backgrounds shape their decisions can help firms stay competitive. Ultimately, by exploring the relationship between CEO backgrounds and organizational outcomes, this research contributes to a deeper understanding of managerial influences within professional services firms, paving the way for more informed practices and improved performance outcomes.

III. Data

A. Sources

The analysis drew upon employment history data from individuals who have previously been employed by Deloitte or EY, encompassing their prior job experiences and roles within either organization. The dataset provides insight into the previous job roles of employees, offering individual yearly records. Each dataset comprises columns including unique identifiers (ID) for employees, their occupations (ONET), job titles, start and end dates of employment, designation of whether the entry pertains to a job within the firm or elsewhere (firm_ind), and additional details (see Appendix A). To further understand the link between CEO backgrounds and employee dynamics, we included data on Deloitte and EY CEOs dating back to 1994. This dataset contains CEO names, their respective firms, tenure lengths, and employment focuses, such as audit, tax, or consulting (see Appendix B).

B. Data Cleaning / Preprocessing

In the data cleaning phase, several measures were taken to fix inconsistencies in the dataset. First, the initial task was to classify records as consulting, auditing, or other based on the ONET occupation code. This classification was derived from solely using the ONET occupation code. The code encompassed a majority of indicators from the job text to sensibly fit into one category so we utilized ONET code instead of job titles to classify records. After classification, rows labeled as 'other' were removed since we only care about these two focuses, auditing and consulting.

After classification, each ID had to be either audit-focused or not. This was determined by calculating numerical values for years of experience in auditing and/or consulting for each record. For example, person ID two could have had three records in the dataset. The first was categorized as audit with five years of experience, the second record was categorized as audit again with one year of experience, and the last record for this individual was categorized as consulting with ten years of experience. In this instance, person ID two had a total of six years of experience in auditing and ten years in consulting. This person therefore would have a label of false, or 0, under audit focused indicator since they had more total years of experience in consulting than auditing. Years of experience were calculated by counting the number of days between the start and end date of each record (see Appendix C).

To address discrepancies from missing data in the end date column, the current date filled this missing data to ensure the calculation of numerical values for years of experience in auditing or consulting was feasible. In some cases, individuals had multiple job entries without end dates, and using today's date to fill in those missing values would exponentially increase the years of experience in both categories. To avoid extreme values in total years of experience in audit and consulting a strategy was devised to infer the end date of the previous job based on the start date of the subsequent job. Despite these efforts, a few records still exhibited extreme values, so they were removed. This occurred because duplicate data or missing start dates persisted for all records of that individual.

In the data processing phase, further steps were taken to refine the dataset and prepare it for analysis. Efforts were made to ensure that columns were in the desired data types, such as DateTime or Integer, to facilitate subsequent analytical tasks, including regression analysis and other statistical techniques.

C. Bias & Outliers

When exploring the categorized data, it was crucial to check for an even distribution of ONET codes in both the audit and consulting groups. Skewed distributions could potentially influence the results, introducing bias into the analysis. However, after a thorough examination and visual representation (see Appendix D), it was observed that the distribution of ONET codes across both groups was comparable. Therefore, the dataset exhibited no discernible bias or outliers, ensuring the integrity of the analysis.

IV. Methodology

The following methodology was applied to each firm separately.

A. Classification

Initial steps involved categorizing each record into audit, consulting, or other groups based on the occupation codes. This categorization aimed to focus the analysis solely on records with either auditing or consulting roles. Records classified as 'other' were excluded from further analysis, as the primary interest lay in auditing and consulting positions. Following this, the years of experience in auditing and consulting were calculated for each individual within their respective groups. Based on the higher experience between the two categories, each person was then labeled as either true or false in the audit_focused_indicator column, indicating their primary focus on auditing or not. This step allowed for the differentiation of the individual's background focus (see Appendix C).

B. Job Changes

1. Exit

In conducting the exit analysis, several steps were followed: All data entries were sorted by date and ID to facilitate sequential analysis. In the data, for each record, there was an indicator (firm_ind) to represent a job within the firm or not. For each individual, it was assessed whether their current job was within the firm and if their subsequent job was outside the firm. This evaluation also considered the condition that the start date of the next job outside the firm followed the end date of the previous one within the firm. If these conditions were met, the 'Exit' column was labeled as true, indicating that the individual had left the firm for another job outside the firm (see Appendix E). Following this, in a new data frame, the data was grouped by occupation and year to calculate the counts of individuals who exited the firm and the total count of records for each occupation and year. Subsequently, the exit rate was calculated for each occupation and year by dividing the number of exits by the total count of records. These calculations resulted in the creation of the exit analysis data frame (see Appendix F). Additionally, in conjunction with the exit analysis data frame, the original data frame was updated to include, for each record, whether the individual had exited the firm or not (see Appendix E). This enhancement provided comprehensive insights into the exit patterns of individuals within different occupations and years.

2. Lateral, Promotion, Demotion

For this analysis, the focus was solely on records of jobs at the firm. Therefore, we began by filtering the data to include only firm job records, as understanding employee movements within the organization was of primary interest. To delve into how individuals transition from one job to another within the firm, we initiated the creation of a new column named 'Origin'. This column captured the job title of each employee's previous position based on their unique ID. Subsequently, we filtered the data to identify transitions between different job titles (ONET codes) where the start date of the new position followed the end date of the previous one. This initiated the creation of a new column named 'Destination'. These transitions were compiled into a new data frame, encompassing columns for both the origin and destination of job titles. We then tallied the occurrences of these transitions. Next, we sought to identify transitions occurring in the opposite direction (from destination to origin) by comparing the origin and destination job titles. If a reverse transition was found, its count was added to the 'Other Direction' column. Finally, we calculated the total number of moves, which comprised the sum of direct and reverse transitions, and computed the ratio of direct transitions to total moves, storing the results in the 'Ratio' column. This process yielded the transition count data frame (see Appendix G).

Following this analysis, a visual of the distribution of the ratios (see Appendix H) from the transitions counts data frame was used to determine how job transitions were categorized, specifically as demotion, lateral, or promotion. After identifying thresholds, each transition was labeled as one of the three categories based on the ratio, providing insights into the nature of employee movements within the firm.

C. Merging Data

Now we're left with two primary data frames awaiting integration. The first data frame comprises ID, ONET, titles, start date, end date, firm indicator, categorization, new end date (with today's date if the end date was missing), total audit years, total consult years, audit-focused indicator, and exit status (see Appendix E). The second data frame contains job transitions, including origin, destination, job move label (lateral, promotion, or demotion), and additional details (see Appendix G).

Since we require individual yearly data, we expanded the first dataframe. This expansion involved duplicating records to represent each year of an individual's employment. For instance, if person ID two held occupation A from 2020 to 2024, the expanded dataframe would include five records for person ID two, each representing a different year from job A. After transposing the data, we needed to include the CEO focus or employment history for each record. To achieve this, a function was devised to incorporate the CEO data, determining the CEO focus at each record and labeling CEO_Focus as either audit, consulting, or tax (see Appendix I). This provided insights into the CEO's background during each record's employment tenure, whether within the firm or not.

Before merging, a new variable was required in the expanded dataframe to have each person's occupation in the following year (see Appendix I). This allowed merging with the transitions' origin and destination variables. Following the creation of this new variable, the transition, and expanded dataframe were combined using union. This approach was chosen as the transition dataframe did not include data if a person's origin and destination were the same, signifying that they remained in the same occupation. If there was no match between the origin and destination when unionizing the tables, it was assigned a 0 (see Appendix J).

After merging all the data, we obtained a unified dataframe comprising ID, ONET, Year, audit history (boolean), consult history (boolean), exit (boolean), CEO focus (consult, audit, or tax), and job move label (0, lateral, promotion, or demotion). Lastly, we transposed the job moves column to obtain a data frame featuring ID, Year, ONET, audit history (boolean), consult history (boolean), exit status (boolean), demotion (boolean), promotion (boolean), lateral (boolean), and CEO focus (tax, consult, or audit) (see Appendix K).

D. Regression

Before performing the regression analysis rows with a CEO focus of 0, indicating missing CEO background data, were identified and dropped from the dataset. Following this, indicators were created to capture specific aspects of employee movements within the firm. For instance, the 'lateral_within' indicator was established to flag records representing lateral moves within the organization. Additionally, a 'shared focus' indicator was introduced to assess the alignment between the CEO's focus and that of the employee (see Appendix L).

To prepare for regression analysis, the datatype of relevant columns was validated to ensure compatibility with statistical procedures. Regression analysis was then conducted for each dependent variable of interest, encompassing factors such as exit, promotion, demotion, lateral moves, and lateral moves within the firm. The regression model incorporated fixed effects for occupation and year, maintaining data granularity at the individual-year level. Furthermore, standard errors were double-clustered at the occupation and year levels to account for potential clustering effects within the data.

Upon analysis, the regression model yielded coefficients and p-values, offering insights into the significance of various factors influencing employee transitions (see Appendix M). Of particular interest was the assessment of the 'shared focus' variable statistical significance across the different dependent variables. This variable is an indicator of alignment between CEOs and employees in either auditing or consulting within these firms. This comprehensive analytical approach provided a nuanced understanding of the factors driving employee movements within the organization, shedding light on the impact of CEO background alignment on employee transitions.

V. Results

A. Deloitte

By honing in on the ‘shared focus’ variable in the regression analysis, it becomes apparent that, for Deloitte, there exists statistical significance in several dependent variables: lateral, promotions, demotions, and lateral movements within the organization. This suggests a correlation between the CEO's ‘shared focus’ and the probability of the dependent variables. Notably, all coefficients were negative, implying that an increase in ‘shared focus’ correlates with a decrease in the likelihood of experiencing the listed dependent variables.

Dependent Variable	Statistically Significant, p-value < 0.05	NOT Significant, p-value > 0.05
Exit		X
Lateral	X (negative)	
Promotion	X (negative)	
Demotion	X (negative)	
Lateral-Within	X (negative)	

B. EY

Examining the ‘shared focus’ variable in the regression analysis for EY, it becomes evident that statistical significance is observed solely for the promotion variable. This implies a correlation between the CEO's ‘shared focus’ and the likelihood of promotions. Notably, the coefficient is positive, indicating that an increase in ‘shared focus’ corresponds to an increase in the likelihood of promotions.

Dependent Variable	**Statistically Significant, p-value < 0.05**	**NOT Significant, p-value > 0.05**
Exit		X
Lateral		X
Promotion	X (positive)	
Demotion		X
Lateral-Within		X

C. Business Impacts

The implications of the results carry weight for the business strategies and operations of both Deloitte and EY. These findings offer crucial insights into the dynamics of employee movements within the firms and shed light on the potential impact of CEO backgrounds on organizational outcomes.

Firstly, the observed variations in results between Deloitte and EY underscore the nuanced nature of organizational dynamics and the influence of contextual factors. While Deloitte exhibits statistical significance across multiple dependent variables, including lateral movements, promotions, demotions, and lateral movements within the organization, EY's results point solely to the promotion variable. This difference could be attributed to several factors, including differences in organizational culture, leadership styles, and strategic priorities between the two firms. Deloitte's broader significance across various dependent variables may reflect a more pronounced influence of CEO background alignment on employee transitions within the organization compared to EY.

The findings directly address the questions posed in the introduction and background sections, particularly regarding the impact of CEO backgrounds on organizational operations and turnover rates. The analysis illuminates how a CEO's prior work experience shapes resource allocation strategies, employee movement patterns, and ultimately, turnover costs within non-related segments of the firms. For instance, the negative coefficients observed in Deloitte's regression analysis suggest that an increase in CEO ‘shared focus’ correlates with a decrease in the likelihood of lateral movements, promotions, demotions, and lateral movements within the organization. Conversely, EY's positive coefficient for the promotion variable implies that a rise in CEO ‘shared focus’ corresponds to an increase in the likelihood of promotions within the firm. These insights provide actionable intelligence for HR and executive leadership teams to optimize workforce allocation strategies, tailor retention efforts, and align organizational priorities with CEO backgrounds effectively.

In practical terms, these findings offer valuable guidance for professional services firms grappling with recruitment challenges and seeking to enhance employee retention strategies, particularly within the auditing domain. By understanding how CEO backgrounds influence organizational dynamics, firms can better navigate talent management processes, mitigate turnover costs, and foster a culture of employee engagement and retention. Moreover, as the accounting profession continues to evolve and diversify, insights from this research can inform strategic decision-making processes, enabling firms to stay competitive in a changing landscape. Ultimately, by unraveling the intricate relationship between CEO backgrounds and organizational outcomes, this study contributes to a deeper understanding of managerial influences within professional services firms.

VI. Conclusion/Next steps

Moving forward, several paths could be explored. Firstly, we could broaden our analysis by looking at more accounting firms to get a comprehensive understanding of how CEO backgrounds impact organizational dynamics within the industry. This could uncover possible patterns across the dependent variables. Additionally, integrating qualitative research methods, such as interviews or surveys with employees and executives, could provide deeper insights into the subjective experiences and perceptions driving workforce allocation strategies and retention efforts within the firms. By embarking on these next steps, this project has the potential to not only deepen our understanding of the impact of CEO backgrounds on organizational operations but also inform evidence-based strategies for enhancing organizational effectiveness and performance in the professional services sector.

VII. Appendix

For presentation efficiency, only Deloitte data will be displayed herein. However, it's important to note that the data from EY mirrors that of Deloitte.

A. Original Employment Data

id	onet	Title1	Title2	start_dt	end_dt	numeric_company_id	deloitte_ind	deloitte_ever
36.0	13-1111.00	Business Analyst (Computer and Mathematical)	Technology Analyst	2018-08-01	NaN	9797218	1	1
36.0	99-1111.00	Solutions Engineer	Intern	2017-06-01	2017-08-01	6980886	0	1
36.0	41-9011.00	Other	Student Ambassador	2016-08-01	2017-05-01	6496747	0	1

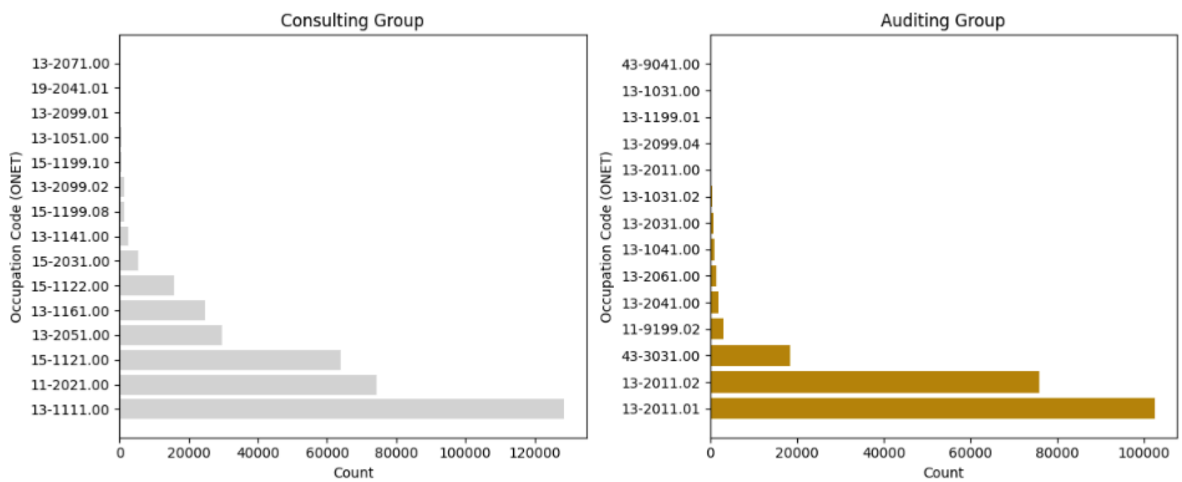
B. CEO Data

Name	Firm	Tenure Start	Tenure End	Tenure Years	Employment History (Audit or Consulting)	Terms
Joe Ucuzoglu	Deloitte	2022	2023	1	Audit	1
Punit Renjen	Deloitte	2015	2022	8	Consulting	2
Barry Salzberg	Deloitte	2011	2015	4	Tax	1

C. Classification, Years of Experience, & Audit-Focused Indicator

id	onet	Title1	Title2	start_dt	end_dt	deloitte_ind	Categorization	new_end_dt	Total_Audit_Years	Total_Consulting_Years	Audit_Focused_Indicator
36.0	13-1111.00	Business Analyst (Computer and Mathematical)	Technology Analyst	2018-08-01	NaT	1	Consulting	2024-03-31 18:14:01.728448	0.000000	5.664613	False
388.0	13-2099.02	Risk Control Consultant	Risk Management Consultant	2005-06-01	2008-04-01	1	Consulting	2008-04-01 00:00:00.000000	0.000000	2.833676	False
1813.0	13-2011.02	Auditor	External Auditor	2007-01-01	2012-05-01	1	Auditing	2012-05-01 00:00:00.000000	5.330595	0.000000	True

D. Distribution of ONET Codes



E. Exit Indicator

id	onet	Title1	Title2	start_dt	end_dt	deloitte_ind	Categorization	new_end_dt	Total_Audit_Years	Total_Consulting_Years	Audit_Focused_Indicator	Exit
36.0	13-1111.00	Business Analyst (Computer and Mathematical)	Technology Analyst	2018-08-01	NaN	1	Consulting	2024-03-31 18:14:01.728448	0.000000	5.664613	False	False
388.0	13-2099.02	Risk Control Consultant	Risk Management Consultant	2005-06-01	2008-04-01	1	Consulting	2008-04-01 00:00:00.000000	0.000000	2.833676	False	False
1813.0	13-2011.02	Auditor	External Auditor	2007-01-01	2012-05-01	1	Auditing	2012-05-01 00:00:00.000000	5.330595	0.000000	True	True

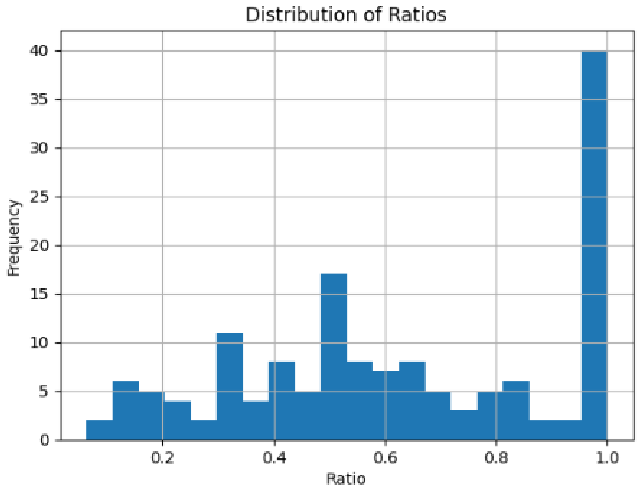
F. Exit Analysis

Occupation	Year	Exit_Count	Total_Count	Exit_Rate
11-2021.00	1900.0	1	1	1.00
11-2021.00	1958.0	0	1	0.00
11-2021.00	1966.0	0	2	0.00

G. Transition Count Analysis

Origin	Destination	Count	Other Direction	Total Moves	Ratio
11-2021.00	11-9199.02	2	3	5	0.400000
11-2021.00	13-1111.00	59	876	935	0.063102
11-2021.00	13-1141.00	1	0	1	1.000000

H. Distribution of Ratios & Thresholds



Thresholds	
Label	**Ratio**
Demotion	0.0 - 0.35
Lateral	0.36 - 0.74
Promotion	0.75 - 1.0

I. Expanded Data Frame

ID	ONET	Year	Audit_History	Consult_History	Exit	CEO Focus	Next_Year_Occupation
3.600000e+01	13-1111.00	2018	0	1	0	Consulting	13-1111.00
3.600000e+01	13-1111.00	2019	0	1	0	Consulting	13-1111.00
3.600000e+01	13-1111.00	2020	0	1	0	Consulting	13-1111.00

J. Unioned Data

ID	ONET	Year	Audit_History	Consult_History	Exit	CEO Focus	Next_Year_Occupation	Origin	Destination	Count	Other Direction	Total Moves	Ratio	Job Move
3.600000e+01	13-1111.00	2018	0	1	0	Consulting	13-1111.00	0	0	0.0	0.0	0.0	0.0	0
3.600000e+01	13-1111.00	2019	0	1	0	Consulting	13-1111.00	0	0	0.0	0.0	0.0	0.0	0
3.600000e+01	13-1111.00	2020	0	1	0	Consulting	13-1111.00	0	0	0.0	0.0	0.0	0.0	0

K. Transposed Union Data

ID	Year	ONET	Audit_History	Consult_History	Exit	Lateral	Promotion	Demotion	CEO Focus
3.600000e+01	2018	13-1111.00	0	1	0	0	0	0	Consulting
3.600000e+01	2019	13-1111.00	0	1	0	0	0	0	Consulting
3.600000e+01	2020	13-1111.00	0	1	0	0	0	0	Consulting

L. Final Dataset - Used for Regression

ID	Year	ONET	Audit_History	Consult_History	Exit	Lateral	Promotion	Demotion	lateral_within	CEO Focus	Shared_Focus
3.600000e+01	2018	13-1111.00	0	1	0	0	0	0	0	Consulting	1
3.600000e+01	2019	13-1111.00	0	1	0	0	0	0	0	Consulting	1
3.600000e+01	2020	13-1111.00	0	1	0	0	0	0	0	Consulting	1

M. Regression Analysis Results Example

OLS Regression Results

Dep. Variable:	Lateral	**R-squared:**	0.004
Model:	OLS	**Adj. R-squared:**	0.004
Method:	Least Squares	**F-statistic:**	130.3
Date:	Wed, 10 Apr 2024	**Prob (F-statistic):**	4.36e-67
Time:	02:37:17	**Log-Likelihood:**	1.3575e+05
No. Observations:	1907555	**AIC:**	-2.715e+05
Df Residuals:	1907551	**BIC:**	-2.714e+05
Df Model:	3		
Covariance Type:	cluster		

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
const	1.316e-05	6.44e-06	2.043	0.041	5.32e-07	2.58e-05
Shared_Focus	-0.0121	0.006	-2.042	0.041	-0.024	-0.000
ID	-1.275e-16	1.13e-17	-11.328	0.000	-1.5e-16	-1.05e-16
ONET	2.333e-09	4.06e-10	5.745	0.000	1.54e-09	3.13e-09
Year	1.586e-05	3.85e-06	4.123	0.000	8.32e-06	2.34e-05

Omnibus:	1485331.327	**Durbin-Watson:**	0.001
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	19461515.616
Skew:	3.931	**Prob(JB):**	0.00
Kurtosis:	16.530	**Cond. No.**	1.81e+16