QUANTIFYING EFFECTS OF COMPANY MERGERS AND ACQUISITIONS ON ONLINE SOCIAL NETWORKS

by
AYŞEGÜL RANA ERDEMLİ

Submitted to the Graduate School of Engineering and Natural Sciences
in partial fulfillment of
the requirements for the degree of Master of Science

Sabancı University
December 2024

QUANTIFYING EFFECTS OF COMPANY MERGERS AND ACQUISITIONS ON ONLINE SOCIAL NETWORKS

Approved by:

. . . .
(Thesis Supervisor)

. . . .

. . . .

Date of Approval: December 16, 2024

ABSTRACT

QUANTIFYING EFFECTS OF COMPANY MERGERS AND ACQUISITIONS ON ONLINE SOCIAL NETWORKS

AYŞEGÜL RANA ERDEMLİ

COMPUTER SCIENCE AND ENGINEERING M.S. THESIS, DECEMBER 2025

Thesis Supervisor: Asst. Prof. Onur Varol

Keywords: social media, finance, mergers and acquisitions, causal inference

Mergers and Acquisitions (M&As), as transformative corporate events, provide companies opportunities to enhance operational efficiency, achieve growth, and strengthen their competitive edge, while affecting a broad range of stakeholders, including employees, executives, shareholders and investors. Considering its reach and influence, social media serves as a powerful tool for investigating events of importance. While previous research utilized social media data in various financial settings, there remains a significant gap in understanding how M&As resonate on the social media accounts of acquirer and target companies and their executives. This study bridges this gap by combining extensive datasets from Thomson Reuters, X (formerly Twitter), and Crunchbase to analyze the impact of M&A events. Employing a Difference-in-Differences (DiD) methodology, we examine post-announcement activity and engagement on the X accounts of companies and executives. Our findings reveal a significant and measurable influence of M&As, reflected in followers, statuses, and engagement metrics of treatment and control groups. Notably, company accounts are more affected than executive accounts. Additionally, target companies and executives experience a pronounced increase in followers and engagement compared to acquirers, while acquirer companies show a significant upward trend in statuses following the event. By uncovering the distinct impacts of M&As on X accounts of key stakeholders—companies and executives—this study offers comparative insights into the dynamics of acquirer and target groups. Moreover, it highlights the effectiveness of causal inference methods, such as DiD, for analyzing the impact of significant events on social media data.

ÖZET

ŞİRKET BİRLEŞMELERİ VE SATIN ALMALARININ ÇEVRİMİÇİ SOSYAL AĞLAR ÜZERİNDEKİ ETKİLERİNİN GÖSTERİLMESİ

AYŞEGÜL RANA ERDEMLİ

BİLGİSAYAR BİLİMİ VE MÜHENDİSLİĞİ YÜKSEK LİSANS TEZİ, ARALIK 2025

Tez Danışmanı: Dr. Öğr. Üyesi Onur Varol

Anahtar Kelimeler: sosyal medya, finans, birleşme ve satın almalar, nedensel çıkarım

Birleşme ve Satın Almalar (M&A'ler), dönüştürücü kurumsal olaylar olarak, şirketlere operasyonel verimliliklerini artırma, büyüme sağlama ve rekabet avantajlarını güçlendirme fırsatları sunar ve çalışanlar, yöneticiler, hissedarlar ve yatırımcılar dahil geniş bir paydaş kitlesini etkiler. Etki alanı ve gücü göz önüne alındığında, sosyal medya, önemli olayları incelemek için güçlü bir araçtır. Daha önceki araştırmalar, sosyal medya verilerini çeşitli finansal bağlamlarda kullanmış olsa da, M&A'lerin satın alan ve alınan şirketler ile yöneticilerinin sosyal medya hesaplarında nasıl yankı bulduğuna dair önemli bir bilgi boşluğu bulunmaktadır. Bu çalışma, Thomson Reuters, X (önceki adıyla Twitter) ve Crunchbase'den elde edilen geniş veri setlerini bir araya getirerek bu boşluğu doldurmayı amaçlamaktadır. Farkların Farkı (Difference-in-Differences) metodunu kullanarak, şirketlerin ve yöneticilerin X hesaplarındaki duyuru sonrası aktivite ve etkileşimlerini analiz ediyoruz. Bulgularımız, takipçi sayıları, paylaşımlar ve etkileşim metrikleri açısından M&A'lerin müdahale ve kontrol grupları üzerinde önemli ve ölçülebilir bir etkisinin olduğunu ortaya koymaktadır. Şirket hesaplarının, yönetici hesaplarına kıyasla daha fazla etkilendiği gözlemlenmiştir. Ayrıca, hedef şirketler ve yöneticiler, satın alanlara kıyasla takipçi ve etkileşimde belirgin bir artış yaşarken, satın alan şirketlerin olay sonrası paylaşımlarında önemli bir artış trendi görülmüştür. Bu çalışma, M&A'lerin şirketler ve yöneticiler gibi kilit paydaşların X hesapları üzerindeki farklı etkilerini ortaya çıkararak, satın alan ve alınan grupların dinamiklerine yönelik karşılaştır-

malı içgörüler sunmaktadır. Bunun yanı sıra, Farkların Farkı yaklaşımı gibi nedensel çıkarım yöntemlerinin, önemli olayların sosyal medya verileri üzerindeki etkisini analiz etmede etkinliğini vurgulamaktadır.

ACKNOWLEDGEMENTS

George R. R. Martin said: *"I have lived a thousand lives and I've loved a thousand loves. I've walked on distant worlds and seen the end of time. Because I read."*
I say: *"I have stayed awake through thousand nights and I've met a thousand wise people from all around the world. I've missed many events, yet with each one, I gained a valuable piece of knowledge in return. I have read the most interesting articles, and seen the brilliant people who wrote them. Because I do research."*

First and foremost, I would like to thank my supervisor, Asst. Prof. Onur Varol, for every minute he has dedicated to me. I feel incredibly fortunate to have had the opportunity to work with an exceptional mentor and scholar like him, in a field I truly love and came to know because of him years ago in his network science course. I have spent two wonderful years learning so much from him, and I am certain that the knowledge he has shared will stay with me forever, guiding me.

I would like to thank Prof. Şerif Aziz Şimşir, whose invaluable guidance in every part of the project made this work and thesis possible, alongside Onur Hoca. I feel incredibly lucky that our paths crossed and that I had the opportunity to work with him. I am also forever grateful to Şeyma Gözüyılmaz, who has been both my peer and mentor throughout the time we have been working.

I cannot thank my family enough for supporting every decision I've made, encouraging me to pursue my wildest dreams and the simplest ones, listening to my illogical concerns, and simply being *there*—which is, undoubtedly, the most important thing. I am blessed to have the most *there* family in the world, and for that, I thank Allah.

I owe a million thanks to Ecem, my roommate, one of my best friends, my twin soul, and fellow computer scientist, who made my master's life enjoyable. I couldn't have made it without you. And to Şeyma, who has been my steadfast companion through all my breakdowns and achievements in academic life, always ready to hug me at both ends of the emotional spectrum—I love you to Saturn and back. My loudest cheerleaders since forever, Ayşenur, Beyza and Nefise; thank you for believing me more than I do in literally everything. I wouldn't even last high school without you.

Last but not least, I would like to express my gratitude to my researcher family, the VRLLab members. It has been the greatest privilege to work among you, to learn from you, and to build friendships with each of you.

Dedication page
To my beloved family.

TABLE OF CONTENTS

LIST OF TABLES .... **xi**

LIST OF FIGURES .... **xiv**

1. INTRODUCTION **1**

2. LITERATURE REVIEW **4**

2.1. The Importance of M&A Events in Finance and Literature 4
2.2. Utilization of Social Media Data for Event Analysis 5
2.3. Utilization of Social Media Data in Finance 6
2.4. Causal Inference and Difference-in-Differences Design 7
2.5. Advantages and Limitations of X Data, Especially Recently 8

3. METHODS AND DATASET **9**

3.1. Datasets 9
3.2. Data Preparation 11
3.2.1. Merging Datasets 11
3.2.2. Data Preprocessing and Feature Extraction 12
3.2.3. Time Series Extraction 13
3.2.4. Normalization 15
3.2.5. Residual Analysis 16
3.2.5.1. Expected Lines and Residuals 16
3.3. Matching 18
3.3.1. Time Series Differences Between Matched Treatment-Control Pairs 23
3.4. Estimating Average Treatment Effects 24

4. RESULTS **30**

4.1. Activities Around M&As 30
4.2. Quantifying Treatment Effect 32
4.2.1. Companies 32

4.2.2. Executives 34

5. DISCUSSION & CONCLUSION **36**

6. ROBUSTNESS EXPERIMENT RESULTS **39**

BIBLIOGRAPHY **47**

APPENDIX B **55**

APPENDIX A **52**

LIST OF TABLES

Table 3.1. **Summary of Organization and Executive Data**: Three columns represent the three main stages of data processing and the change in data size. **After Merging** refers to merging datasets and eliminating non-conforming accounts, **After Matching Pairs** refers to matching the most similar treatment and control accounts, and **After Outlier Removal** refers to eliminating outliers and longest consecutive fills. **Control Total** is put for the first column since the control accounts are not categorized as target or acquirer before they are matched with such labeled treatment accounts. Control Total in the other columns are just the summation of Control Acquirer and Control Target values. 11
Table 3.2. **Summary of Matching Features and Preprocessing** 19
Table 3.3. **Temporal Features of Matching Data** T being the M&A event date, different temporal features from before the event were extracted in order to find similar social account pairs between treatment and control groups. 20
Table 3.4. Cluster Information of Business Categories and Examples 20
Table 3.5. **Interpretations of Coefficient Magnitudes and Signs** 27
Table 3.6. Statistical differences between treatment and control pre-trend slope distributions for Organizations and Executives. Stars (*) indicate statistically significant p-values ($p < 0.05$). 29

Table 4.1. **Input Data to Difference-in-Differences Model** 30

Table A.1. Title Standardization for Executives 53
Table A.2. Degree Type Standardization for Executives Mapping 53
Table B.1. **Companies - Followers** Robustness Analysis Results for Different Time Ranges with Before Event Range as (-100, 0) 55
Table B.2. **Companies - Statuses** Robustness Analysis Results for Different Time Ranges with Before Event Range as (-100, 0) 56

Table B.3. **Companies - Daily Engagement** Robustness Analysis Results for Different Time Ranges with Before Event Range as (-100, 0) 57
Table B.4. **Executives - Followers** Robustness Analysis Results for Different Time Ranges with Before Event Range as (-100, 0) 58
Table B.5. **Executives - Statuses** Robustness Analysis Results for Different Time Ranges with Before Event Range as (-100, 0) 59
Table B.6. **Executives - Daily Engagement** Robustness Analysis Results for Different Time Ranges with Before Event Range as (-100, 0) 60
Table B.7. **Companies - Followers** Robustness Analysis Results for 7 Day Difference Time Series Values........ 61
Table B.8. **Companies - Statuses** Robustness Analysis Results for 7 Day Difference Time Series Values........ 62
Table B.9. **Companies - Daily Engagement** Robustness Analysis Results for 7 Day Difference Time Series Values 63
Table B.10. **Executives - Followers** Robustness Analysis Results for 7 Day Difference Time Series Values........ 64
Table B.11. **Executives - Statuses** Robustness Analysis Results for 7 Day Difference Time Series Values........ 65
Table B.12. **Executives - Daily Engagement** Robustness Analysis Results for 7 Day Difference Time Series Values 66
Table B.13. **Companies - Followers** Robustness Analysis Results for Last 7 Day Mean Difference Time Series Values 67
Table B.14. **Companies - Statuses** Robustness Analysis Results for Last 7 Day Mean Difference Time Series Values 68
Table B.15. **Companies - Daily Engagement** Robustness Analysis Results for Last 7 Day Mean Difference Time Series Values 69
Table B.16. **Executives - Followers** Robustness Analysis Results for 7 Day Mean Difference Time Series Values 70
Table B.17. **Executives - Statuses** Robustness Analysis Results for 7 Day Mean Difference Time Series Values 71
Table B.18. **Executives - Daily Engagement** Robustness Analysis Results for 7 Day Mean Difference Time Series Values........ 72
Table B.19. **Companies - Followers** Robustness Analysis Results for Multiple After Event Coefficients 72
Table B.20. **Companies - Statuses** Robustness Analysis Results for Multiple After Event Coefficients 73

Table B.21. **Companies - Daily Engagement** Robustness Analysis Results for Multiple After Event Coefficients 73
Table B.22. **Executives - Followers** Robustness Analysis Results for Multiple After Event Coefficients 73
Table B.23. **Executives - Statuses** Robustness Analysis Results for Multiple After Event Coefficients 73
Table B.24. **Executives - Daily Engagement** Robustness Analysis Results for Multiple After Event Coefficients 73

LIST OF FIGURES

Figure 3.1. **Schematic overview of the methodology**. Main datasets are merged (a) and divided into treatment and control datasets (b) including information from all three. Similarity between treatment and control samples calculated considering their features at the time of M&As (c) and the most similar pairs are matched for the causal inference analysis (d). Time series around the event dates (-120, +120) were extracted for number of followers, statuses and daily engagement for every entry (e). Logarithmic transformation were applied to time series signals and then min-max normalization standardize each signal (f). Residuals for the time series (deviations from the expected trend line created with the information before the event) were measures for every entry (g). Finally, DiD model applied to residual data of followers, statuses, daily engagement for all entries in order to observe the significant change in treatment accounts after the event (h). 10

Figure 3.2. **Raw Follower Time Series of *tripadvisor* (Treatment Acquirer)** Cumulative number of followers of tripadvisor's X account between the years 2011-2021. There are missing data at some dates. Red vertical line represents the deal date of an M&A which tripadvisor was an acquirer company in. Gray area illustrates the time window we used in our analysis. 13

Figure 3.3. **Forward (a) and backward (b) filling methodology examples**. Backward filling is applied only if there are no valid data before -T to forward fill with. Black numbers being actual values at the time point, green values indicate the first valid values before (a) or in (b) the event range that is used to forward (a) or backward (b) fill the missing values in the beginning of the event range. Blue is used to indicate the time points forward filled normally with the values within the range. 14

Figure 3.4. **Outliers - Longest Consecutive Fills** Outliers in the 85 percentile are colored in red, which are the data where there are very long consecutive series filled with forward-backward filling approach explained in Figure 3.3 15
Figure 3.5. **Processed Follower Time Series of *tripadvisor* (Treatment Acquirer)** Transformations and preprocessing applied on raw time series described in the previous sections. After the extraction of time series around the event date (Figure 3.2), missing date values are imputed with forward and backward filling approach (Figure 3.3) and a continuous time series of length 241 is created (a), then the raw values are log10 transformed (b), and min-max normalization is applied (c) (see also Section 3.2.4), an expected line and according residuals (Section 3.2.5) from the normalized time series is extracted before the main analysis. 17
Figure 3.6. **Outliers - Feature Similarity in Matched Pairs** Outliers decided with a z-score of 2.5 in terms of the distance from 45° line (indicating a perfect match with no difference between the value of the feature of treatment and control) are colored in red, which are the treatment-control pairs which have a significant difference in on of their X account features. 21
Figure 3.7. **Control Types in Matched Pairs** X axis being the treatment and Y axis being the control, individual datapoints represent the difference between matched pairs. Green color indicates treatments matched with original controls while blue color is used to identify the matches with the type controlv2 companies (See Section 3.2.1). 22
Figure 3.8. **Distribution of Features Before and After Pairwise Matching - Companies** 22
Figure 3.9. **Distribution of Features Before and After Pairwise Matching - Executives** 23
Figure 3.10. **Mean Time Series Differences: Companies** 24
Figure 3.11. **Mean Time Series Differences: Executives** 24
Figure 3.12. **Difference-in-Differences Design Illustrated** 25
Figure 3.13. **Pre-trend Slope Distributions of Companies** 28
Figure 3.14. **Pre-trend Slope Distributions of Executives** 28

Figure 4.1. **Treatment Effect**. Mean residuals of change in followers, statuses and daily engagement time series of companies (a, b, c) and executives (d, e, f) demonstrating the difference between treatment and control groups following the event date. 31

Figure 4.2. **Model Results - Companies** Diff-in-diff model results in terms of coefficient significance of β, γ and ρ. Statistically significant values of coefficients are shown colored and statistically insignificant values are all shown in gray. Before event range is constant and (-50, 0) for all experiments. Results for acquirer (a, b, c) and target (d, e, f) companies are shown in two rows. 33
Figure 4.3. **Model Results - Executives** Diff-in-diff model results in terms of coefficient significance of β, γ and ρ. Statistically significant values of coefficients are shown colored and statistically insignificant values are all shown in gray. Before event range is constant and (-50, 0) for all experiments. Results for acquirer (a, b, c) and target (d, e, f) executives are shown in two rows. 35

Figure 6.1. **Model Results - Different Time Frames Robustness Analysis for Companies** Diff-in-diff model results for companies with different time ranges than presented in the main results (Figure 4.2). Before time range is constant and (-50, 0) for all experiments. After time range for longer time periods (up to (0, 100) is shown in order to see the long-term effect. 40
Figure 6.2. **Model Results - Different Time Frames Robustness Analysis for Executives** Diff-in-diff model results for executives with different time ranges than presented in the main results (Figure 4.3). Before time range is constant and (-50, 0) for all experiments. After time range for longer time periods (up to (0, 100) is shown in order to see the long-term effect. 41
Figure 6.3. **Model Results - Different Time Frames Robustness Analysis for Companies** Diff-in-diff model results for companies with different time ranges than presented in the main results (Figure 4.2). Before time range being constant and (-100, 0), asymmetric after time ranges are used to see the the effect in time. 42
Figure 6.4. **Model Results - Different Time Frames Robustness Analysis for Executives** Diff-in-diff model results for executives with different time ranges than presented in the main results (Figure 4.3). Before time range being constant and (-100, 0), asymmetric after time ranges are used to see the the effect in time. 43

Figure 6.5. **Model Results - Different Time Frames Robustness Analysis for Companies** Diff-in-diff model results for companies with different time ranges than presented in the main results (Figure 4.2). Symmetric before and after time ranges are used to see the the effect of short and long time periods. 43
Figure 6.6. **Model Results - Different Time Frames Robustness Analysis for Executives** Diff-in-diff model results for executives with different time ranges than presented in the main results (Figure 4.3). Symmetric before and after time ranges are used to see the the effect of short and long time periods. 44
Figure 6.7. **Model Results - Different Time Series Values Robustness Analysis for Companies** Diff-in-diff model results for companies with different time series values unlike residuals used in the main results (Figure 4.2). Every time point is the difference of the normalized value from the 7 day before. 44
Figure 6.8. **Model Results - Different Time Series Values Robustness Analysis for Companies** Diff-in-diff model results for companies with different time series values unlike residuals used in the main results (Figure 4.2). Every time point is the difference of the normalized value from the mean of the last 7 days. 45
Figure 6.9. **Model Results - Multiple Rho - Robustness Analysis for Companies** Diff-in-diff model results for companies with different time ranges and additional features, namely multiple rhos and gammas for segregated time ranges after the event to how the effect's significance change over time. 46
Figure A.1. **Business Category Distribution of Companies** Business category distribution among 1365 companies included in DiD analysis. 52
Figure A.2. **Distribution of Executive Features** Feature distribution among 1898 executives included in DiD analysis. 52
Figure A.3. **Distribution of Unique Deal Dates Across Years** Among unique deal dates of companies (595) and executives (362) in our data, most of the deals belong to the years before 2019. 53
Figure A.4. **Distribution of Unique Deal Dates Across Months** Among unique deal dates of companies (595) and executives (362) in our data, there are no significant differences in the number of the deals announced in different months. 54

Figure A.5. **Distribution of Unique Deal Dates Across Weekdays** Among unique deal dates of companies (595) and executives (362) most of the deals were announced on Monday. Meanwhile very little of the deals were announced during the weekend. 54

1. INTRODUCTION

Merger and Acquisitions (M&As) are major corporate events that enable companies to improve operating efficiency, accelerating their external growth, increase their power in the competition with the rivals and benefit from economies of scale (DePamphilis, 2021). Considered an important part of company growth strategy, M&As affect many stakeholders such as employees, executives, shareholders, investors, regulators, customers, suppliers, consultants, and competitors. In this study, we examine the reflections of the potential changes in corporate strategy on social media, particularly on X (formerly Twitter), when a merger event is first shared with the public.

When a shocking incident occurs such as natural disasters (Pourebrahim, Sultana, Edwards, Gochanour & Mohanty, 2019; Sakaki, Okazaki & Matsuo, 2010), terrorist attacks (Starbird, Maddock, Orand, Achterman & Mason, 2014) and events like award ceremonies or sport events (Kim, Kim, Keegan, Kim, Kim & Oh, 2015), their impact can be observed on social media since public attention shift toward them. As a widely used micro-blogging platform, X provides a rich data of people's conversation on different topics, specifically important events. Leveraging this textual and numerical data for event detection and analysis can be effectively achieved using causal inference techniques.

Causal inference methods are extensively employed in data analytics, particularly for assessing the impact of specific events. While most studies utilizing social media data rely on observational findings, causal inference methods offer valuable insights when natural experiments are identified to evaluate an event's effects (Phan & Airoldi, 2015; Sismeiro & Mahmood, 2018; Yang & Peng, 2022).

The real-time nature of X makes it an indispensable tool for companies to monitor customer sentiment, address their concerns promptly, and track competitors' activities to inform strategic decisions (Blankespoor, Miller & White, 2014; Hollebeek, Glynn & Brodie, 2014; Rietveld, Van Dolen, Mazloom & Worring, 2020). Furthermore, the immediate reactions to corporate announcements on these platforms provide managers with valuable insights, enabling them to assess the effectiveness and precision of their strategic choices (Cookson, Niessner & Schiller, 2022). Given its expansive reach and influential capabilities, social media serves as a powerful channel for companies to publicize critical events, such as mergers and acquisitions (M&As). However, despite the dynamic role of social media in corporate communication, there remains a significant gap in understanding how such major corporate events resonate on these platforms post-announcement. This study aims to bridge that gap by exploring the interplay between corporate announcements and social media responses.

There are previous studies focused on the social media activity of acquirer companies, executives and investors in different financial contexts. Social media accounts of the target companies in any financial event let alone M&A events are rarely investigated.

Rather than utilizing textual data for sentiment analysis as in most of the social media studies (Batrinca & Treleaven, 2015), we focused on numerical time series data extracted from X metadata to identify the changes around M&A events. We used three types of time series data, namely cumulative follower and statuses counts, and daily engagement. While follower and statuses counts are directly taken from the daily snapshots of the Twitter metadata; daily engagement time series was created by us, taking the total number of retweets, quotes, mentions and replies for each day. While change in number of cumulative statuses indicate an activity by the account (company or executive) itself, a change in follower and engagement would indicate the response of the public and whether if their attention shifts toward the account following an M&A event.

Similar to our usage of social media data, there are studies in finance literature different contexts used number of Tweets as a measure of Twitter activity (Behrendt & Schmidt, 2018) while assessing the effect of investor sentiment on stock return volatility, utilized Thomson Reuters M&A data in their research on Twitter announcements of M&A events (Mazboudi & Khalil, 2017), examined acquirer executives' general activeness of the accounts derived from the total number of Tweets and retweets (Wang, Lau & Xie, 2021) while measuring the tendency to take part in M&As.

In this study, we try to address two main research questions:

- How do M&A events influence measurable activities (status counts) and engagement metrics (followers, retweets, quotes, mentions, replies) on X accounts of companies and executives involved in the deals?

- To what extent do the effects of M&A events differ between companies and executives, and how do these differences manifest between acquirer and target groups?

To the best of our knowledge, ours is the first study to combine three large datasets from Thomson Reuters, X, Crunchbase; investigating activity and engagement of both companies and executives while considering both acquirer and target side of M&A events. Our study not only discovers the impact of M&A events on social media activity of the two important stakeholders, companies and executives involved, but also provides a comparative insight of how acquirer and target companies, companies and executives act after the event. Our main results suggest that the impact of M&As are more visible in company X accounts compared to executives meanwhile target group's social media activity and engagement is more affected than the acquirer group's. The most significant results are seen on daily engagement change for both companies and executives.

2. LITERATURE REVIEW

Social media, particularly X (formerly Twitter), has become one of the richest data sources for assessing the impact of significant events and observing public attention to them. The rise of social media as an information source has notably influenced the finance sector, specifically the interactions between companies and investors within capital markets. Researchers in finance and data science have been uncovering signals within social media data that could potentially predict financial situations, such as future security prices. Social media engagement shapes how companies are perceived by investors and customers, reflects trust in management teams, and captures sentiment toward their products and services. Mergers and Acquisitions (M&As) are major corporate events that impact companies, executives, competitors, customers, suppliers, and regulators. Consequently, scholars have explored the implications of company and executive social media engagement in the context of these events. This section provides an analysis of the social media and finance literature relevant to our work.

2.1 The Importance of M&A Events in Finance and Literature

Mergers and acquisitions (M&As) have become a crucial external growth strategy for acquiring companies. The impact of M&As extends beyond the acquirer and target firms to include their executives, employees, shareholders, investors, competitors, and regulators. In some cases, high-profile mergers have even driven structural changes within entire industries and prompted international responses (Piesse, Lee, Lin & Kuo, 2022), as seen in Elon Musk's acquisition of Twitter or Disney's acquisition of Fox.

The increasing frequency and length of M&As over recent decades have fueled extensive academic research in this area (Gaughan, 2015). Studies have explored the success and failure, motives, and effects of M&A events across various contexts, often from multidisciplinary perspectives. Topics include the human and psychological aspects (Cartwright & Cooper, 2018; Seo & Hill, 2005), the influence of cultural values and differences (Ahern, Daminelli & Fracassi, 2015), the role of director gender (Levi, Li & Zhang, 2014), and human resources implications (Schuler & Jackson, 2017). Additionally, researchers have examined business ethics (Lin & Wei, 2006), as well as the presence and activity of investor (Wang & Lau, 2019), executive (Wang et al., 2021), and company (Mazboudi & Khalil, 2017) accounts and the effect of merger rumors (Jia, Redigolo, Shu & Zhao, 2020) on social media.

2.2 Utilization of Social Media Data for Event Analysis

Event detection and analysis on the effects of the events on online social networks has been widely studied with varying event topics and methodologies. Different events such as elections (Najafi, Mugurtay, Zouzou, Demirci, Demirkiran, Karadeniz & Varol, 2024), natural disasters (Qu, Huang, Zhang & Zhang, 2011; Vieweg, Hughes, Starbird & Palen, 2010), protests (Ansah, Liu, Kang, Liu & Li, 2020; Varol, Ferrara, Ogan, Menczer & Flammini, 2014), terrorist attacks (Starbird et al., 2014), award ceremonies (Wallach, 2014), or sport games (Kassens-Noor, Vertalka & Wilson, 2019) attract public attention and impact social media activities. There are numerous works focused on detection of disruptive events -which are considered important events need to be immediately detected to preserve public safety- by investigating the textual data, increase in the frequency of certain words (bursting effect) and word-pairs with NLP techniques.

Alsaedi & Burnap (2015) examined the significant role of both temporal and textual features in event detection using data from X, particularly for identifying disruptive events. Temporal features include word frequencies from the most recent Tweets, while textual features encompass various aspects of Tweet content, such as content similarity; the ratio of retweets, mentions, hashtags, links, and URLs within a given time frame; a dictionary of trigger words, and Tweet sentiments. Their findings indicate that incorporating textual features improve the performance of the baseline model created with temporal features, proving the effectiveness in detecting any event. When all textual features and temporal features combined, they deliver a strong performance in identifying disruptive events.

Studies with valuable findings across many different disciplines highlight the pivotal role of social media's vast and diverse data in event detection and analysis. By leveraging both temporal and textual features extracted from social media platforms, researchers have shown a notable ability to identify impactful events in real time. Among these platforms, X stands out as a micro-blogging network where events are instantly reflected, serving as a news source for millions and even journalists (Broersma & Graham, 2013). This makes X one of the most dynamic sources of data for event analysis, providing unmatched opportunities for real-time monitoring and insights.

2.3 Utilization of Social Media Data in Finance

Social media has become a platform where financial news and events are widely discussed. Consecutively, the social media accounts of stakeholders such as investors, executives, companies and shareholders on social media has been the subject of recent research in finance. Interestingly, Jayasuriya & O'Neill (2021) showed that not only the activity and engagement of the accounts, but even the presence of social media itself has an impact on financial market.

On the investor side of the stock market studies, Behrendt & Schmidt (2018) analyzed the effect of Twitter sentiment of individual investors on the intraday and Twitter activity on stock return volatility where Twitter activity is denoted by number of tweets. Their findings suggest that this effect is statistically significant yet economically neglectable.

In their work focused on the companies on social media, Mazboudi & Khalil (2017) suggested that announcing financial events such as M&As on Twitter had become an important part of investor relations and found that larger acquirers tend to disclose acquisition announcements on Twitter more. They also used M&A data from Thomson Reuters. Their observations also emphasized that high-technology industries are more likely to be early-adopters of social media.

Focusing on investigating Twitter accounts of what they refer to as *social executives*, Wang et al. (2021) found that the presence of Twitter accounts and their activeness of senior executives increases the tendency of acquirer firms to take part in M&A deals. They used static variables of (1) presence of accounts (2) general activeness of the accounts derived from the total number of Tweets and retweets. An interesting study by Li, Liang & Tang (2024) suggested that the CEOs which have social media accounts are more likely to make risky and unethical choices that would benefit themselves.

Not only the aforementioned major stakeholders but more specific groups like minority shareholders has also been the subjects of studies. Chen, Liu, Liu, Chen & Zhang (2024) analyzed the engagement of minority shareholders on social media and its effect on M&A outcomes in the specific case of China. Their findings suggest that increase in the post-merger firm value of the acquirer companies can be associated with the high minority shareholder engagement on social media.

Unlike scholars who examined the activities of financial stakeholder accounts, Fan, Talavera & Tran (2020) explored the relationship between Twitter bot accounts and bot posts with stock market prices, showed evidence of both bot and human Tweets having significant relation with stock features. They also claimed that the impact of human Tweets is more powerful.

2.4 Causal Inference and Difference-in-Differences Design

Causal inference methods are widely used in data analytics, specifically for measuring an event's effect on time series data. A common causal inference approach mostly used in economics (Slaughter, 2001), finance (Derrien & Kecskés, 2013), marketing (Deng, Xu, Li, Liu & Shi, 2019), public policy (Branas, Cheney, MacDonald, Tam, Jackson & Ten Have, 2011), education (Hanushek & W ößmann, 2006) and health (Goodman-Bacon & Marcus, 2020) literature is the difference-in-differences design.

While most studies on social media primarily present observational findings, causal inference methods can be effectively applied to social media data when a natural experiment is identified, allowing researchers to assess the impact of specific events (Phan & Airoldi, 2015; Sismeiro & Mahmood, 2018; Yang & Peng, 2022). The difference-in-differences (DiD) approach, in particular, has gained prominence in multidisciplinary research involving social media, addressing topics such as mental health (Braghieri, Levy & Makarin, 2022) and political science (Horta Ribeiro, Hosseinmardi, West & Watts, 2023).

Although much of the existing literature examines the effect of social media events or activities on external outcomes, a growing body of research focuses on using the DiD approach to uncover how events influence social media activities and engagement. Recent studies demonstrate the potential of this method for analyzing shifts in engagement metrics and user behavior resulting from significant events (Ershov & Mitchell, 2020; Hsu & Tsai, 2022; Zhu, Cao, Xie, Yu, Chen & Huang, 2023).

2.5 Advantages and Limitations of X Data, Especially Recently

With hundreds of millions of monthly active users, X (formerly Twitter) is one of the most popular micro-blogging platforms where the majority of the posts consists of plain text. Limitless number of topics are discussed daily in this giant social network, providing a rich textual data for research. Applying techniques like sentiment analysis, topic modeling, spatial analysis, content analysis, big data mining; Twitter data is widely used for research on politics, stock markets, disaster analysis, social movements, disease surveillance, marketing, human behavior and more (Karami, Lundy, Webb & Dwivedi, 2020).

After Elon Musk's acquisition of Twitter on October 27, 2022, the data sharing policies of the micro-blogging platform has changed in the direction that limits academic research (Varol, 2023). Disabling free data access in March 2023, X provided tiers ranging from $100 to $42,000 a month and started to reject many researchers who requested academic API-access. Reuters reported that many academic projects were canceled, suspended or changed direction due to new regulations (Dang, 2023).

3. METHODS AND DATASET

3.1 Datasets

To investigate the effects of mergers and acquisitions on social media by tracking online activities and gathering detailed information about the companies and M&A events, we obtained datasets from various sources.

Crunchbase is an online platform that provides best-in-class live data powered by a unique community of contributors, partners, and in-house data experts. The data was retrieved as of October 2021. It consists of detailed information about companies and their employees. We initially collected data for 1,593,672 companies and 1,245,268 employee entries. We extracted useful features and links for the X profiles of companies and C-level executives.

The Securities Data Company (SDC) database of Thomson Reuters is one of the world's most trusted sources of information. The dataset includes all merger and acquisition activities with announcement dates ranging from 2010 to September 2021, encompassing a total of 43,748 deals. All deal values in this dataset are greater than 10 million dollars. We obtained details related to each M&A event, such as deal dates, target companies, and acquiring companies.

X (formerly Twitter) is a micro-blogging platform that offers content on a variety of topics. We collected statuses (tweets) and the daily number of tweets posted by the accounts of companies and executives obtained from the Crunchbase dataset. To measure attention towards these companies, we also retrieved detailed data on the number of quotes, retweets, replies, and mentions about these accounts (these four will be mentioned as *engagement* from now on) in addition to followers. In total, X account data for 11,050 companies and 25,873 executives were collected.

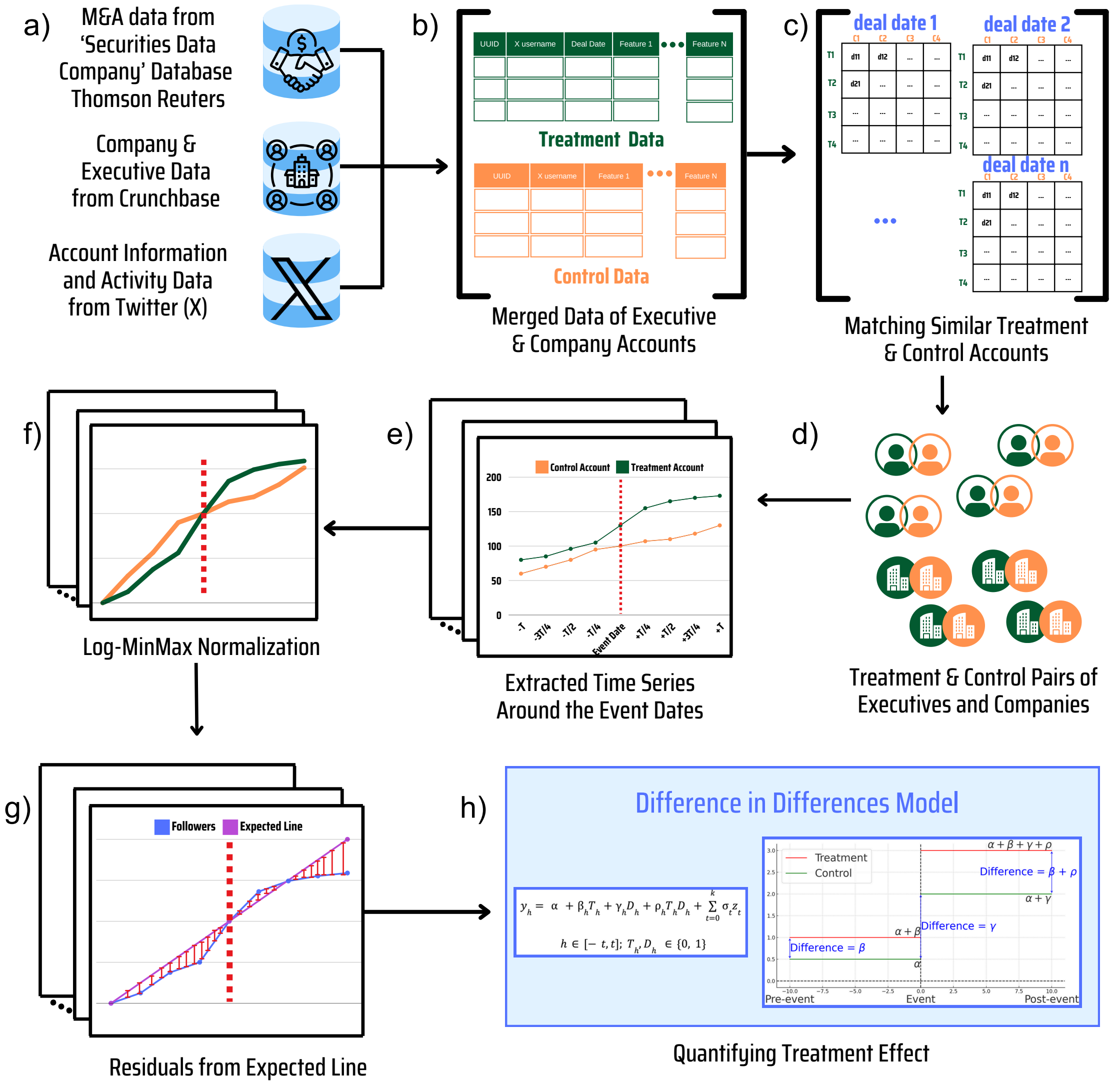

Figure 3.1 **Schematic overview of the methodology**. Main datasets are merged (a) and divided into treatment and control datasets (b) including information from all three. Similarity between treatment and control samples calculated considering their features at the time of M&As (c) and the most similar pairs are matched for the causal inference analysis (d). Time series around the event dates (-120, +120) were extracted for number of followers, statuses and daily engagement for every entry (e). Logarithmic transformation were applied to time series signals and then min-max normalization standardize each signal (f). Residuals for the time series (deviations from the expected trend line created with the information before the event) were measures for every entry (g). Finally, DiD model applied to residual data of followers, statuses, daily engagement for all entries in order to observe the significant change in treatment accounts after the event (h).

These three extensive datasets were merged considering inclusion criterion detailed in the following sections.

Table 3.1 **Summary of Organization and Executive Data**: Three columns represent the three main stages of data processing and the change in data size. **After Merging** refers to merging datasets and eliminating non-conforming accounts, **After Matching Pairs** refers to matching the most similar treatment and control accounts, and **After Outlier Removal** refers to eliminating outliers and longest consecutive fills. **Control Total** is put for the first column since the control accounts are not categorized as target or acquirer before they are matched with such labeled treatment accounts. Control Total in the other columns are just the summation of Control Acquirer and Control Target values.

Category	After Merging	After Matching Pairs	After Outlier Removal
		Companies	
Acquirer	462	431	330
Target	412	405	304
Control Acquirer	-	537	390
Control Target	-	478	342
Control Total	1669	1015	732
Total (Companies)	2543	1851	1366
		Executives	
Acquirer	519	475	431
Target	261	250	222
Control Acquirer	-	930	812
Control Target	-	509	433
Control Total	9462	1439	1245
Total (Executives)	10242	2164	1898

3.2.1 Merging Datasets

We applied preprocessing steps to the data during and after merging the information from the three datasets and filtered with a few inclusion criteria to ensure reliable information for the analysis (Figure 3.1a). We ensured that each entry included in our time series analysis had the following information fully completed: industry and employee count for companies, degree, title, and gender for executives, and X account details with existing account data (followers, statuses, and engagement time series) for both. Another criterion was to only include companies based in the US, as they represented the majority of entries with complete information. We labeled companies and executives as treatment or control, with treatment indicating a record of an M&A event and control indicating no such record (Figure 3.1b). The records for companies that had not participated in any M&A deals were even fewer than those for treatment companies. To ensure a sufficient pool of control companies for the next steps, we created an additional control group, *controls from companies that had engaged in M&A* (controlv2). For inclusion in this group, a treatment company's Twitter data could only be used as a control entry if the event date of the matched treatment was at least two years prior to the earliest deal of the controlv2 company.

Additionally, we excluded treatment entries where a company or executive was involved in two M&A events within the same year to avoid overlapping time series in our analysis. However, we retained deals involving the same company if they occurred in non-overlapping time periods. In their study on the engagement of minority shareholders on social media and its impact on M&A outcomes, Chen et al. (2024) analyzed only the first M&A event for companies with multiple acquisitions within the same year. Similarly, we identified companies with multiple M&A records within a one-year window. The potential for lasting effects from the first event to influence the time series of the second, or signals from the second event affecting the time series of the first, led us to exclude both entries rather than retaining only the first event's data.

3.2.2 Data Preprocessing and Feature Extraction

During preprocessing prior to matching, we applied several exclusion criteria to ensure data quality. Specifically, we excluded entries that (i) lacked complete information on X accounts or the selected Crunchbase features (see Table 3.2 for details), and (ii) involved companies or executives participating in more than one M&A event within the same year. Following the matching process, we further refined the data by excluding outlier pairs—those matched by the global optimum criterion but showing significant differences in their matching features (see Figure 3.6).

After extracting time series data around event dates for each entry, we cleaned the data excluding entries which (i) contained excessively long consecutive fills to avoid analyzing data that was predominantly imputed, and (ii) exhibited unnatural X activity changes, which could indicate bulk deletions, bot activity, or artificial follower acquisitions. Figure 3.4 highlights outlier cases in consecutive fills within the followers and statuses time series. Since daily engagement data typically had consistent daily records, exclusions based on this criterion were unnecessary.

3.2.3 Time Series Extraction

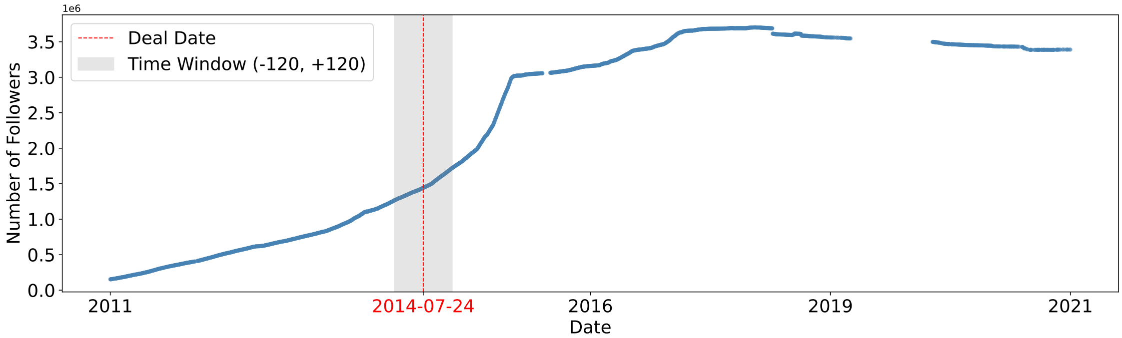

Figure 3.2 **Raw Follower Time Series of *tripadvisor* (Treatment Acquirer)** Cumulative number of followers of tripadvisor's X account between the years 2011-2021. There are missing data at some dates. Red vertical line represents the deal date of an M&A which tripadvisor was an acquirer company in. Gray area illustrates the time window we used in our analysis.

We extracted time series from social media data to capture activity and engagement changes (Figure 3.1e). Each tweet contains metadata about users, and we combined the daily statistics of followers, statuses, and engagement, as we were interested in how these metrics changed around the M&A events. The time window for the time series was set to include 120 days before and 120 days after the event, resulting in a total of 241 time points. An example of time series extraction from a raw data of *tripadvisor*'s X followers is illustrated on Figure 3.2.

$$\text{daily\_engagement} = \text{retweeted}_t + \text{mentioned}_t + \text{quoted}_t + \text{replied}_t \tag{3.1}$$

Time series for followers and statuses were recorded as the cumulative number of followers and tweet counts of the account, representing a snapshot of each day. Meanwhile, daily engagement data was not directly available in the X metadata, so it was generated by summing the daily counts of different engagement types. Specifically, for each time point in the time series, the number of mentions, retweets, quotes, and replies received on that day were aggregated to form the daily engagement metric.

The time series were standardized for subsequent analysis and comparison. First, they were aligned around the M&A event date (deal date) for each treatment instances (see Section 3.3) for how deal dates were assigned for control entries).

Next, missing values in the time series were filled using forward filling to ensure a continuous sequence. If no reference value was available for the initial days of the series, backward filling was applied using the first valid value in the series. The data gathered from Twitter was sparse, with some dates missing values. Specifically, we did not scrape data for certain days if there was no activity or change in follower count for the account. As a result, when the event date and surrounding dates were selected, some of the required dates lacked values in the data. To address this, we initially assigned -1 to the missing dates to create a complete time series array of size $2 \times T + 1$. These placeholders were then filled using the approach illustrated in Figure 3.3.

(i) If the first value in the time series array was present (i.e., not -1), we forward filled the missing values with the closest available value before them. (ii) If the first value within the (-T, +T) range was missing, we located the last valid value before the range and forward filled the missing values with that value (Figure 3.3a). (iii) If no valid values existed before the range, we backward filled the initial indices with the first valid value found within the range (Figure 3.3b). After applying these strategies in all three cases, we forward filled the remaining missing values as needed.

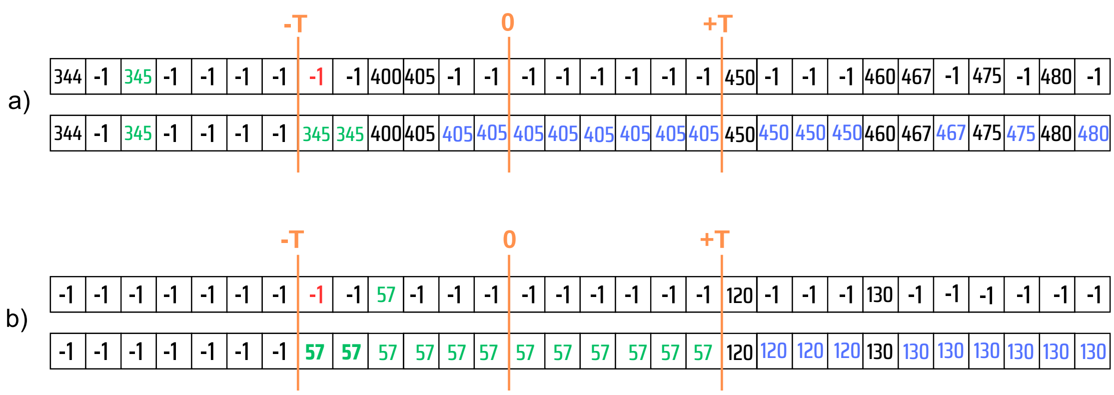

Figure 3.3 **Forward (a) and backward (b) filling methodology examples**. Backward filling is applied only if there are no valid data before -T to forward fill with. Black numbers being actual values at the time point, green values indicate the first valid values before (a) or in (b) the event range that is used to forward (a) or backward (b) fill the missing values in the beginning of the event range. Blue is used to indicate the time points forward filled normally with the values within the range.

The inclusion criteria for accounts in relation to the extracted time series required that they be active, defined as having at least two changes in the cumulative number of followers and statuses both before and after the event. Finally, normalization was applied to the raw time series data (see Section 3.2.4).

After extracting the time series, we eliminated dramatic outliers, which showed sudden, unnatural changes possibly due to major changes in the platform or inorganic activities observed for these accounts. An example of such an outlier can be an account that gained $10,000$ followers in a single day. Although the acquisition of followers or the bulk deletion of tweets can be linked to significant company events, such as M&As, we excluded these scenarios from the analysis.

Next, we identified accounts where a very long consecutive period in the time series required forward or backward filling. We removed the time series with the longest consecutive filled periods to ensure a dataset with more natural patterns and actual values for most dates (Figure 3.4).

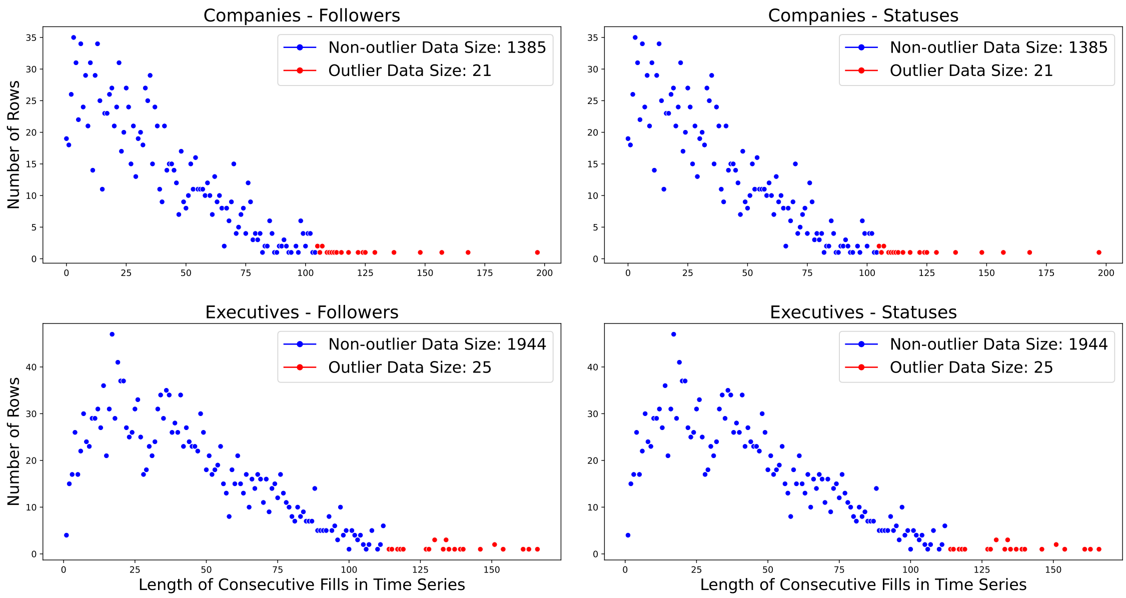

Figure 3.4 **Outliers - Longest Consecutive Fills** Outliers in the 85 percentile are colored in red, which are the data where there are very long consecutive series filled with forward-backward filling approach explained in Figure 3.3

3.2.4 Normalization

In the extracted X time series data, followers, statuses, and engagement were all represented as raw numbers, with followers and statuses being cumulative snapshots of the day. Since the X accounts varied in size and often differ with multiple orders of magnitude, the raw data was normalized to standardize the analysis (Figure 3.1f). First, a logarithmic transformation in base 10 was applied to the values across all time points. Second, a slightly modified min-max normalization was performed. To prevent the introduction of bias from the data after the event, the minimum and maximum values were calculated using only the time-series data before the event, and then the normalization was applied to the entire time series using these values.

3.2.5 Residual Analysis

To investigate the difference between treatment and control groups in terms of deviations from the normal trend of an account's activity (defined as the trend before the event), residuals of the normalized time series were calculated (Figure 3.1g). First, the natural trend (denoted as the expected line) for each entry was determined using a line equation based on the first and last points before the event. Then, the expected value for each time point was computed according to this line equation. Finally, the residual time series were obtained by calculating the deviation from the expected trend for each entry's time series, specifically by subtracting the expected value at each time point from the actual normalized value of the day. Following subsection shows the process in detail.

3.2.5.1 Expected Lines and Residuals

Expected behavior of each entry was calculated in the form of a line equation retrieved by the minimum and maximum points before the event.

1.1 For each entry's normalized followers, statuses and daily engagement time series, two points were taken, which are the very first point and the last point before the event (0th and T-1st, T being 120). x_i is the index of the time point and y_i is the value on that index, where i is 1 or 2 for min and max values, respectively.

$$x_1, y_1 = 0, \text{ time\_series}[0]$$

$$x_2, y_2 = T - 1, \text{ time\_series}[T-1]$$

1.2 Slope m of the line is calculated via the chosen two points:

$$m = \frac{y_2 - y_1}{x_2 - x_1}$$

1.3 Bias b is calculated:

$$b = y_1 - m \cdot x_1$$

1.4 A function of expected value for y is created:

$$f_{\text{tstype}} = m \cdot x + b$$

1.5 For every index of the time series, the value of that index is found via the function of expected values, resulting in the *expected_line* of that entry (row).

1.6 For every index of the time series, the residual value of that index is found via subtracting the actual time series values from the *expected_line* values.

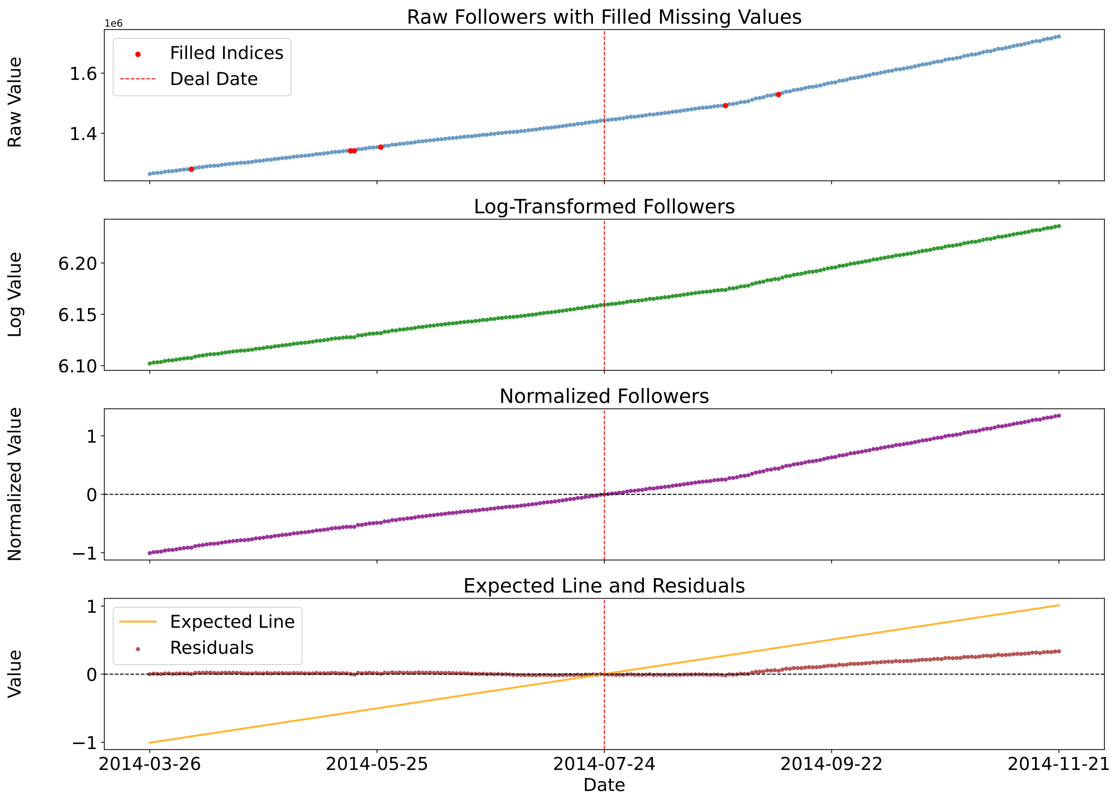

Figure 3.5 **Processed Follower Time Series of *tripadvisor* (Treatment Acquirer)** Transformations and preprocessing applied on raw time series described in the previous sections. After the extraction of time series around the event date (Figure 3.2), missing date values are imputed with forward and backward filling approach (Figure 3.3) and a continuous time series of length 241 is created (a), then the raw values are log10 transformed (b), and min-max normalization is applied (c) (see also Section 3.2.4), an expected line and according residuals (Section 3.2.5) from the normalized time series is extracted before the main analysis.

3.3 Matching

The main objective of this study is to investigate whether an M&A event can *cause* the activity and engagement of treatment company/executive X accounts to differ from those of control accounts, with the M&A event serving as the intervention on the treatment group. To explore this causal relationship in time series data, causal inference methods were applied. We had treatment data along with their event dates, and we identified companies and executives with no M&A history to serve as a control group. However, directly utilizing control data with a random date range for their time series is not a viable approach. In a case which we randomly choose a control group, an observed difference between time series of treatment and control groups cannot be reliably related to the M&A event.

Therefore, a crucial step was to find *similar accounts* to the treatment group, where company/executive characteristics and X account features would act as *confounding variables*. A common approach in causal inference is *matching*, which pairs treatments with controls based on similarity determined by these confounding variables. Since our analysis focus on X time series, the main criteria for detecting similarity were the features of the X accounts.

To perform causal inference analysis and quantify the changes observed around the M&A events for the treatment group (companies and executives involved in M&A events), we identified a control group by matching entries from accounts without an M&A activity for 241 days (Figure 3.1c-d). We repeated the same time series analysis on both groups and quantified the observed differences between the treatment and control groups.

A pairwise matching was conducted separately for companies and executives to find the closest possible control entry for every treatment entry. One of the reasons of performing this matching process was to set a hypothetical *event date* for control accounts, which served as the reference date for the time series construction. After matching, each control entry was assigned the event date of its treatment counterpart, and the time series were aligned around this date.

For both executive and company accounts, we extracted features from their posts. Temporal data like number of followers and statuses extracted from profile details of tweet activities. We consider values 120 days prior to the M&A activity. Unlike changes in profile metadata, online activities show more burstiness and can only be captured by individual posting activities. To estimate the average engagement, we consider all posts between 120 and 150 days before the M&A activity. We calculated the total engagement (obtained by number of retweets, mentions, quotes, and replies) for each tweet and their average were used as average engagement. Additionally, *business category* for companies and *gender*, *highest degree*, and *title* for executives were also considered during the matching process. Preprocessing done on the title and degrees of executives are shown in Appendix Tables A.1 and A.2. Distribution of all financial features across the company and executive data used in the main analysis after matching are visualized in the Appendix Figures A.1 and A.2.

Table 3.2 **Summary of Matching Features and Preprocessing**

Type	Feature	Explanation	Preprocessing
Common Feature	*twitter_account_size*	Cumulative follower count 120 days before the event date (event date will be the matched treatment's event date for controls)	log10 transformation
Common Feature	*tweet_count*	Cumulative tweet count 120 days before the event date (event date will be the matched treatment's event date for controls)	log10 transformation
Common Feature	*average_engagement*	Mean engagement between 150 days before the event and 120 days before the event.)	log10 transformation
Company Feature	*business category*	List of industries that can be related to the company.	743 unique categories were grouped using NLP and clustering. Resulting 10 general categories were one-hot-encoded. (See appendix for general grouping)
Executive Feature	*title*	Job title in the company, only c-level executives were used (see appendix for full list of considered title types)	one-hot-encoding
Executive Feature	*gender*	Gender of the executive (M/F)	one-hot-encoding
Executive Feature	*highest degree*	Educational degree of the executive (see appendix for full list of considered degree types)	one-hot-encoding

Table 3.2 outlines the features used in the matching procedure, along with their preprocessing and scaling methods. Common features, which include numerical social media-related attributes for both executives and companies, were utilized to construct the distance matrix that determined pairwise matches between treatment and control entries (see Section 3.3 for details on the distance matrix and its application). Most features underwent straightforward transformations, such as *log10*

Table 3.3 **Temporal Features of Matching Data** T being the M&A event date, different temporal features from before the event were extracted in order to find similar social account pairs between treatment and control groups.

Feature	Definition
Account Size	$\text{account\_size} = \text{followers}_t,\ t = T - 120$
Tweet Count	$\text{tweet\_count} = \text{statuses}_t,\ t = T - 120$
Average Engagement	$\text{average\_engagement} = \frac{1}{30}\sum_{t=T-150}^{T-120}(\text{retweeted}_t + \text{mentioned}_t + \text{quoted}_t + \text{replied}_t)$

Table 3.4 Cluster Information of Business Categories and Examples

Cluster Number	Cluster Label	Example Categories
0	video, media, entertainment	esports, social news, video advertising
1	service, travel	delivery service, mobile payments, travel accommodation
2	games, drones, sports	drones, saas, podcast
3	health, care	health diagnostics, personal health, advice
4	data, cloud	file sharing, agtech, marketing automation
5	management, social	public transportation, tutoring, business information
6	energy, water	water transportation, renewable energy, laser
7	web, apps, hardware	cad, linux, ux design
8	food, home	outdoor advertising, shoes, craft beer
9	design, industrial	automotive, mechanical design, nutraceutical

scaling and one-hot encoding. However, preprocessing the *business category* feature posed a greater challenge due to the presence of 743 unique categories. To address this, we applied NLP techniques to cluster the categories into 10 business groups. The resulting clusters were labeled with the assistance of ChatGPT3.5, as summarized in Table 3.4.

Since we quantify the impact of M&A events from the X activity, it was crucial to match similar types of X accounts as control counterparts for each treatment. Dynamic nature of the X profiles makes the matching procedure more challenging, because we are not only matching by static features but also align the time of the event and snapshot of features at that particular time. For control groups, we have to consider different hypothetical event times for each account in treatment group. Distance matrices were created for each event date, where (i) treatment entries included in the treatment axis were those that had an event on that date, and (ii) the control axis consisted only of controls with available X data on that date and satisfied the condition of having at least two common one-hot encoded features for executives and one for companies with the treatment intersection (Figure 3.1c). Each cell was filled with the distance between the 3-dimensional vectors (Equation 3.2) formed using *account size*, *tweet count*, and *average engagement* for the treatment and control entries (since these features are time-dependent, the event date of the intersecting treatment was used to calculate the control's features).

(3.2)

$$\text{distance}_{a,b} = \|\boldsymbol{v}_a - \boldsymbol{v}_b\|, \quad \boldsymbol{v}_a = \begin{bmatrix} \text{account\_size}_a \\ \text{tweet\_count}_a \\ \text{average\_engagement}_a \end{bmatrix}, \quad \boldsymbol{v}_b = \begin{bmatrix} \text{account\_size}_b \\ \text{tweet\_count}_b \\ \text{average\_engagement}_b \end{bmatrix}$$

$$a \in \text{treatment},\ b \in \text{eligible\_controls}_a$$

After creating the distance matrices for each date, the Hungarian algorithm (Kuhn, 1955) was used to find the best pairings within each matrix by minimizing the distance. Following the matching procedure i) pairwise differences in feature vectors were calculated and ii) outliers were analyzed and eliminated to ensure strongly similar treatment-control pairs.

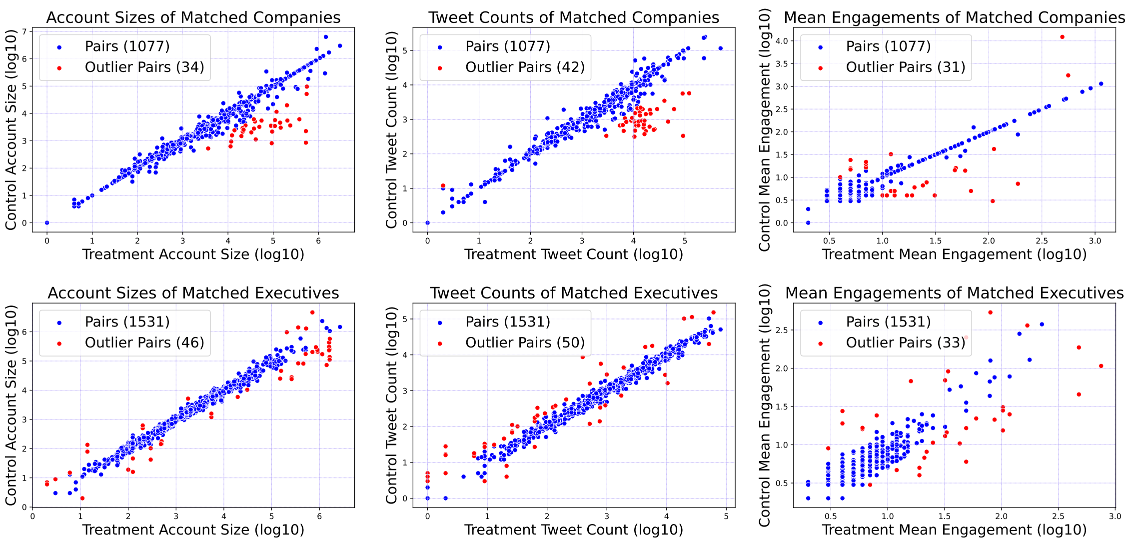

Figure 3.6 **Outliers - Feature Similarity in Matched Pairs** Outliers decided with a z-score of 2.5 in terms of the distance from 45° line (indicating a perfect match with no difference between the value of the feature of treatment and control) are colored in red, which are the treatment-control pairs which have a significant difference in on of their X account features.

Due to the limited availability of company entries that had no M&A events while meeting our inclusion criteria, we expanded the control group to include company data from before any M&A event occurred. This addition to the control group,

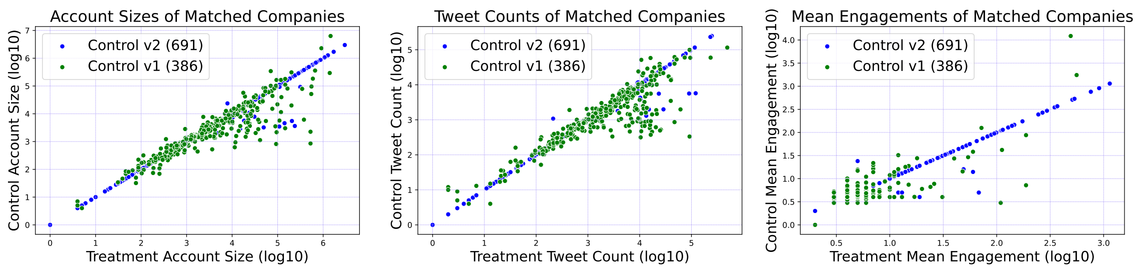

Figure 3.7 **Control Types in Matched Pairs** X axis being the treatment and Y axis being the control, individual datapoints represent the difference between matched pairs. Green color indicates treatments matched with original controls while blue color is used to identify the matches with the type controlv2 companies (See Section 3.2.1).

referred to as *controlv2*, allowed us to increase the pool of matched pairs. Figure 3.7 illustrates the distribution of matched pairs, differentiating between companies with no record of M&A activity (controlv1) and those included based on data from at least two years before their first recorded M&A event (controlv2). This approach ensured a more comprehensive control group while maintaining alignment with our analysis requirements.

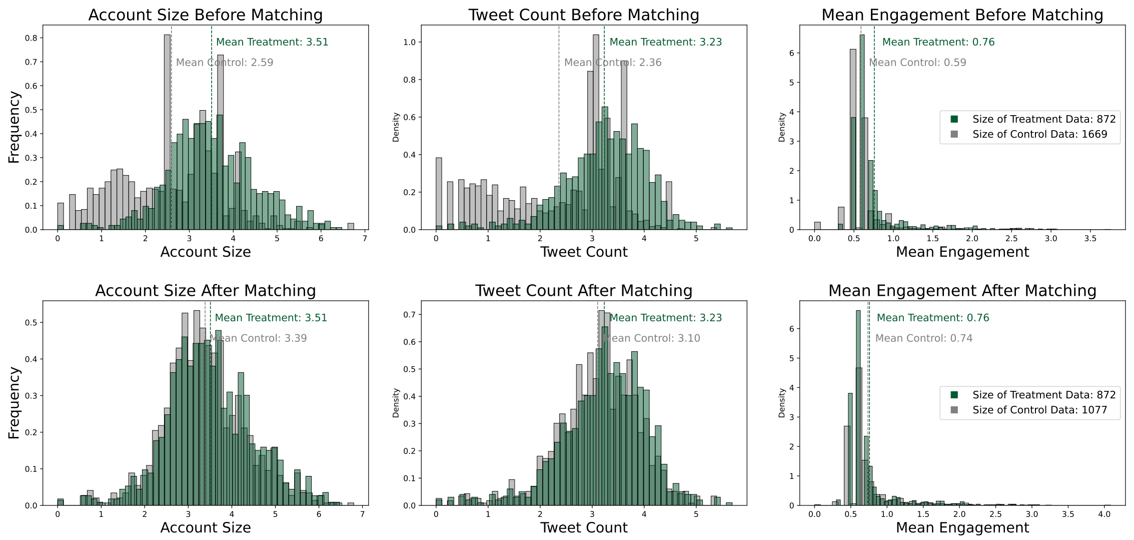

Figure 3.8 **Distribution of Features Before and After Pairwise Matching - Companies**

Figures 3.8 and 3.9 demonstrate the distribution of social media features across treatment and control groups, both before and after the matching process. The visual alignment observed in the distributions post-matching indicates that pairwise matching successfully balanced the treatment and control groups. This adjustment ensures that the control group entries closely resemble the treatment group entries in terms of feature similarity. By excluding control entries that lacked suitable

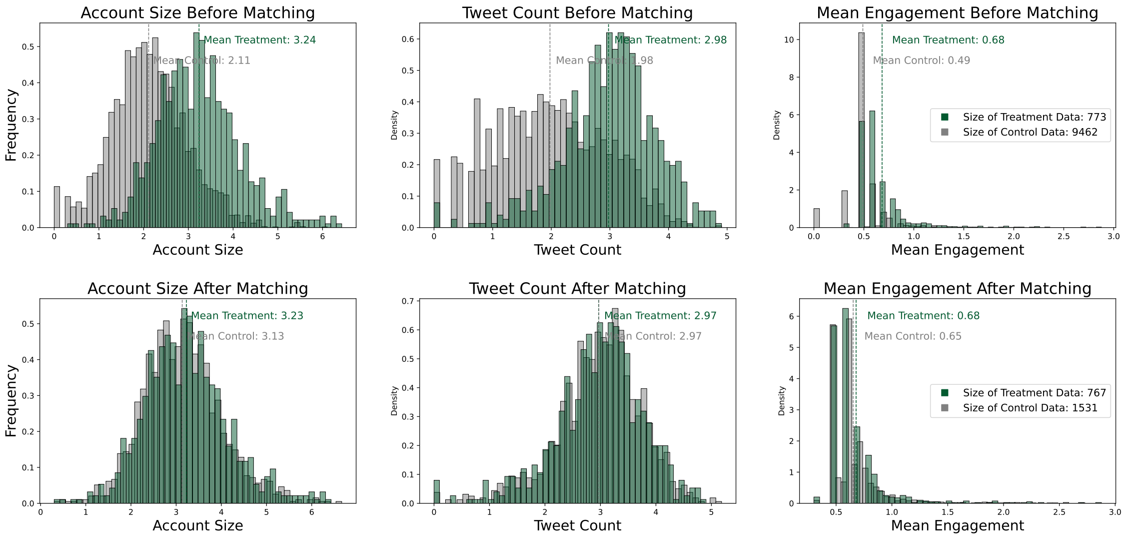

Figure 3.9 **Distribution of Features Before and After Pairwise Matching - Executives**

counterparts in the treatment pool, the matching process enhanced comparability between the groups, thereby providing a robust foundation for subsequent time series analysis and modeling efforts.

3.3.1 Time Series Differences Between Matched Treatment-Control Pairs

As described in 3.3, treatment and control entries were matched one to one prioritizing their closeness in terms of using *account size*, *tweet count*, and *average engagement*. This was a naive assumption about the similarity of Twitter accounts around the same date. We would expect the similarity between the follower, status, and engagement counts would decrease as the time passes since a single value of a specific date is not an indicator of how the activity of that account will proceed. Nevertheless, we wanted to see how the difference between follower, status, and daily engagement counts between matched pairs change in general since these three types of time series are used in the main analysis described in Section 3.4. Figures 3.10 and 3.11 show the mean time series differences between pairs. We can observe that daily engagement time series of pairs are more similar than their follower and status time series around the event date. Meanwhile, the quality of executive matchings seem to be better in terms of follower and status counts, supporting the feature similarity of account size and tweet counts (Figure 3.6).

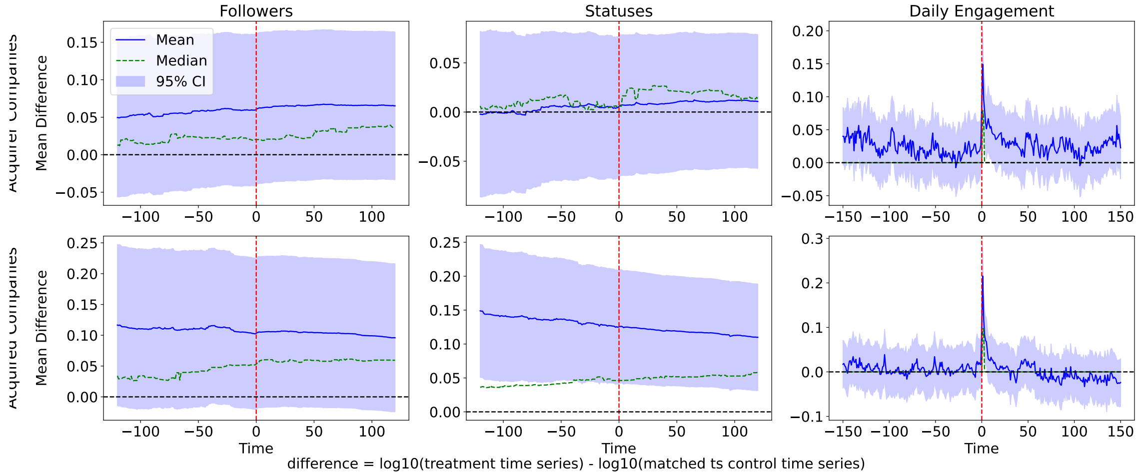

Figure 3.10 **Mean Time Series Differences: Companies**

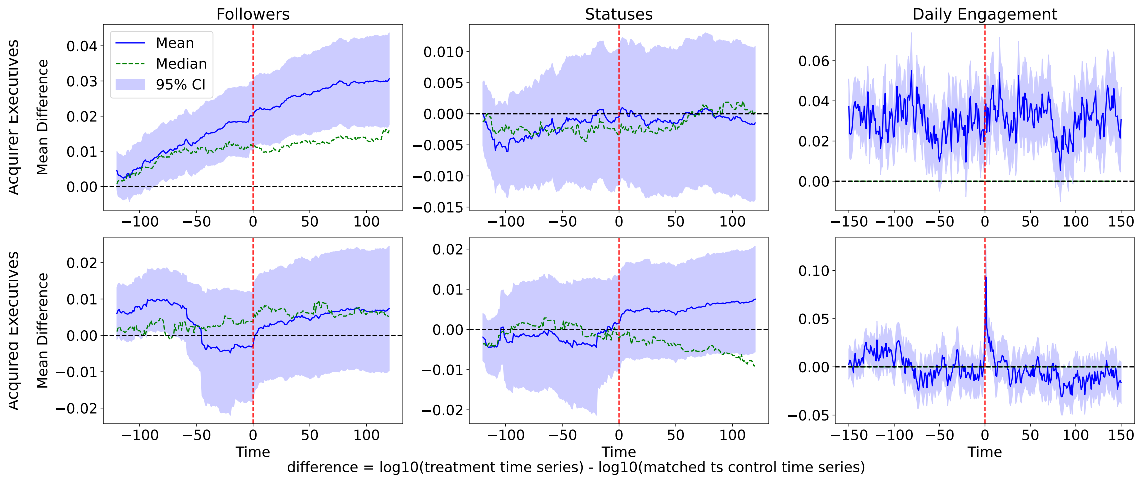

Figure 3.11 **Mean Time Series Differences: Executives**

3.4 Estimating Average Treatment Effects

To quantify the impact of M&A events on social media, we developed a linear regression model to estimate the treatment effect using a difference-in-differences (DiD) approach (Figure 3.1h).

As a causal inference method widely used in event analysis on time series data, DiD provides an statistical insight on whether a treatment differs from the control group in the presence of an event. In order to observe the difference between treatment and control time series after the event, there should be ideally minimal difference between the two groups before the event. Meanwhile, we expect trend of the control group to show no change after the event.

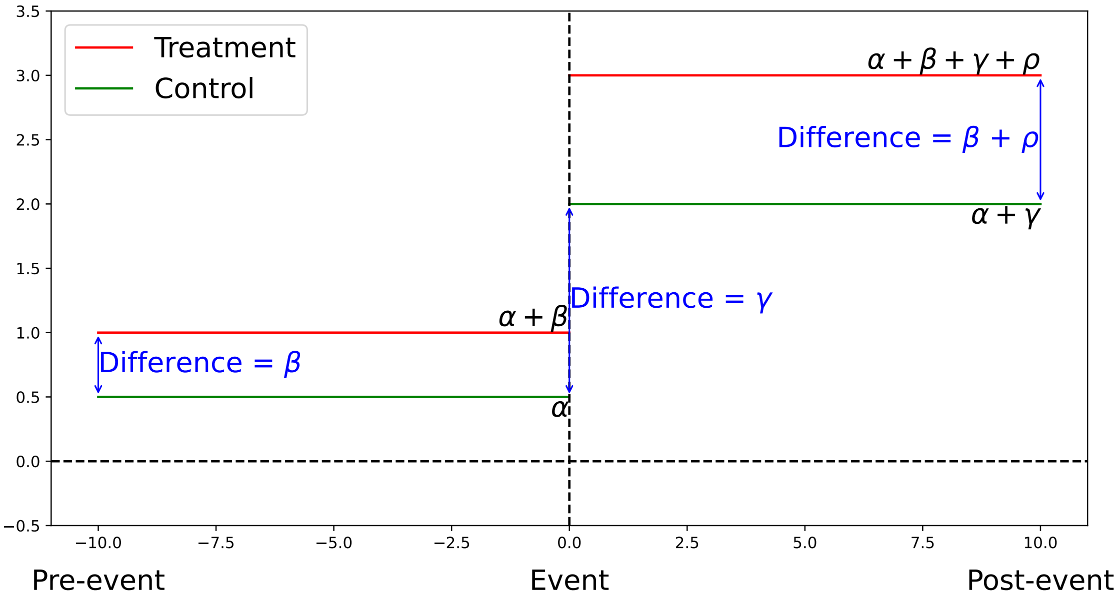

Figure 3.12 **Difference-in-Differences Design Illustrated**

$$y_h = \alpha + \beta_h T_h + \gamma_h D_h + \rho_h T_h D_h + \sum_{t=0}^{k} \sigma_t z_t \tag{3.3}$$

$$h \in [-50, 50];\ T_h, D_h \in \{0, 1\}$$

We constructed the model considering residual at time point h as the y_h value to be estimated. We also tested alternative models with different y_h values, such as the difference from the value 7 days prior, and their results are presented in the Appendix.

In Equation 3.3, y_h represents a residual value at time point h in an account's time series (followers, statuses or daily engagement). T is a binary indicator representing whether the account belongs to the treatment or control group while β is the treatment coefficient indicating the difference between control and treatment before the event. D is a dummy variable indicating whether the time point is before or after the event and γ is its coefficient capturing the difference between time points before and after the event for the control group. $T \times D$ is the interaction term, and coefficient ρ measures the effect of the event on the treatment group compared to the control group. Finally, z_t represents the control variables, such as *account size*, *employee count*, and one-hot encoded *categories* for companies and *account size*; one-hot encoded categorical features *title*, *degree*, *gender* used for executives, along with time components *year*, *month*, and *day* for both companies and executives.

Here is an example to explain difference-in-differences design further:
Case 1: A treatment entry before the event:

$$\begin{aligned} y_a &= \alpha + \beta \cdot 1 + \gamma \cdot 0 + \rho \cdot 1 \cdot 0 + \sum_{t=0}^{k} \sigma_t z_t \\ &= \alpha + \boldsymbol{\beta} + \sum_{t=0}^{k} \sigma_t z_t \end{aligned}$$

where $a < 0$, $T_a = 1$ and $D_a = 0$.

Case 2: A control entry before the event:

$$\begin{aligned} y_b &= \alpha + \beta \cdot 0 + \gamma \cdot 0 + \rho \cdot 0 \cdot 0 + \sum_{t=0}^{k} \sigma_t z_t \\ &= \alpha + \sum_{t=0}^{k} \sigma_t z_t \end{aligned}$$

where $b < 0$, $T_b = 0$ and $D_b = 0$.

Case 3: A treatment entry after the event:

$$\begin{aligned} y_c &= \alpha + \beta \cdot 1 + \gamma \cdot 1 + \rho \cdot 1 \cdot 1 + \sum_{t=0}^{k} \sigma_t z_t \\ &= \alpha + \boldsymbol{\beta} + \boldsymbol{\gamma} + \boldsymbol{\rho} + \sum_{t=0}^{k} \sigma_t z_t \end{aligned}$$

where $c \geq 0$, $T_c = 1$ and $D_c = 1$.

Case 4: A control entry after the event:

$$\begin{aligned} y_d &= \alpha + \beta \cdot 0 + \gamma \cdot 1 + \rho \cdot 0 \cdot 1 + \sum_{t=0}^{k} \sigma_t z_t \\ &= \alpha + \boldsymbol{\gamma} + \sum_{t=0}^{k} \sigma_t z_t \end{aligned}$$

where $d \geq 0$, $T_d = 0$ and $D_d = 1$.

Differences between treatment and control entries:

$$\text{Difference 1: } y_a - y_b = \boldsymbol{\beta}$$

$$\text{Difference 2: } y_c - y_d = \boldsymbol{\beta} + \boldsymbol{\rho}$$

$$\text{Difference-in-Differences: } (y_c - y_d) - (y_a - y_b) = \boldsymbol{\rho}$$

Difference-in-Differences value ρ symbolizes the difference of the differences between treatment and control after and before the event. Thus, the significance of ρ will show how significantly differ the treatment group from the control group after time point T, i.e. in the presence of an event.

Since we are confident that matched control and treatment pairs have similar X accounts and non-time-dependent features, in an ideal scenario, there should not be any significant differences between the two groups (treatment and control) before the event. Likewise, the control group should not show a significant change after the event date since the event does not impact them. Hence, neither β nor γ should be statistically significant in the ideal scenario.

Table 3.5 **Interpretations of Coefficient Magnitudes and Signs**

Coefficient Case	**Interpretation**
Negative β	Treatment group shows a lower trend before the event compared to the control group.
Negative γ	Control trend decreases after the event.
Positive ρ	Treatment is positively affected by the event compared to the control's situation before and after the event.
Low absolute value of β	Control and treatment had very little difference before the event, indicating a good matching.
Low absolute value of γ	Control shows no-to-small change before and after the event.
High absolute value of ρ	Significantly positive impact is observed on the treatment as a result of the event.

The coefficient ρ being statistically significant and high in magnitude compared to the other coefficients would suggest that the event caused a notable change on the treatment group which is not observed on the control group. Thus, our main hypothesis is that ρ should be significant in most experiments, as M&A events are major events likely to influence X activity and public attention for companies and executives.

An essential assumption for employing the Difference-in-Differences (DiD) design to measure the impact of an event is the parallel trends assumption. This assumption states that, in the absence of an intervention, the treatment and control groups would have followed similar trends over time. To evaluate this assumption, researchers often rely on both visual and statistical analyses of pre-event trends. A common visual approach involves plotting the average values of the outcome variable (y) over time for both groups to ensure that their trends are reasonably parallel prior to the event (Schiozer, Mourad & Martins, 2020). In our analysis, Figure 4.1 illustrates a reasonably parallel trend in the residual time series for the treatment and control groups before the intervention.

To further assess the parallel trends assumption, we calculated the slopes of the pre-event trends for the individual time series via linear regression. Figures 3.13 and 3.14 reveal that the general distributions of treatment and control slopes for log-transformed time series values are similar, with the distribution of slope differences between treatment-control pairs centered around zero. Moreover, statistical tests confirm that, except for one experimental group—acquirer executives, which yielded insignificant results in the DiD analysis—there are no statistically significant differences between the pre-trend slopes of the treatment and control groups across all other data groups.

These findings provide robust evidence that the treatment and control groups exhibit parallel trends before the event date, thereby validating the assumption necessary for the reliability of the DiD design.

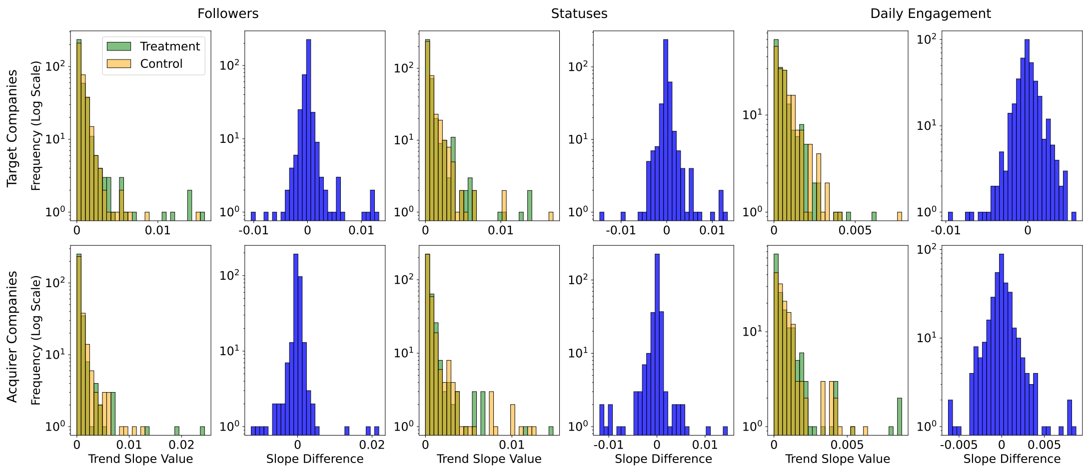

Figure 3.13 **Pre-trend Slope Distributions of Companies**

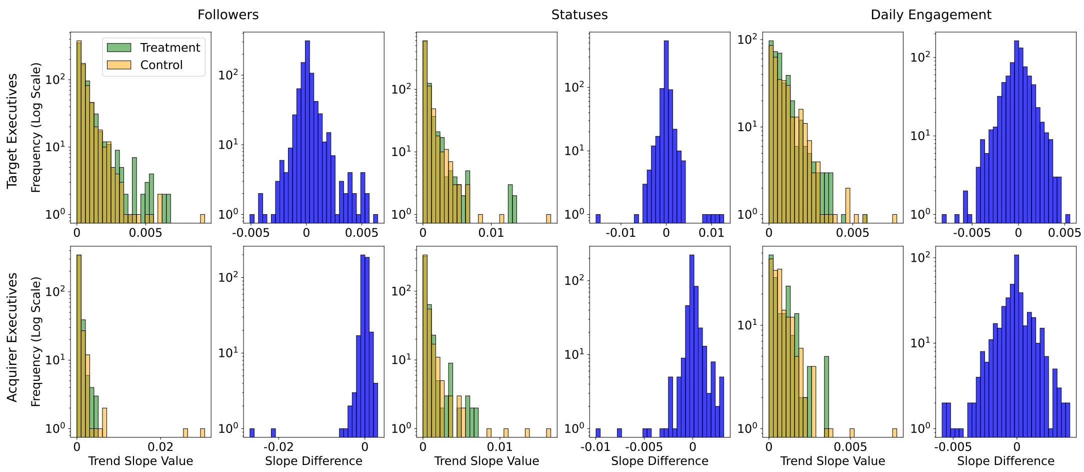

Figure 3.14 **Pre-trend Slope Distributions of Executives**

Table 3.6 Statistical differences between treatment and control pre-trend slope distributions for Organizations and Executives. Stars (*) indicate statistically significant p-values ($p < 0.05$).

Group	**Type**	**Column Type**	**Treatment Median**	**Control Median**	**KS p-value**	**Mann-Whitney p-value**
Organizations	Acquirer	Followers	0.000319	0.000354	0.5069	0.8024
		Statuses	0.000353	0.000393	0.3999	0.3811
		Daily Engagement	0.000000	0.000000	0.6849	0.3786
	Acquired	Followers	0.000243	0.000269	0.6032	0.2291
		Statuses	0.000315	0.000326	0.4794	0.3079
		Daily Engagement	0.000000	0.000000	0.8946	0.8893
Executives	Acquirer	Followers	0.000326	0.000275	**0.0335***	**0.0057***
		Statuses	0.000284	0.000291	0.3536	0.5056
		Daily Engagement	0.000000	0.000000	0.0554	0.5149
	Acquired	Followers	0.000220	0.000223	0.8195	0.8917
		Statuses	0.000233	0.000229	0.3781	0.4360
		Daily Engagement	0.000000	0.000000	0.2221	0.1836

4. RESULTS

In this section, we present findings from the difference-in-differences (DiD) model. We applied this model to time series data representing the dynamic changes for followers, statuses, and daily engagement of 1,366 companies and 1,898 executives (Table 4.1). Our initial findings on the effects of M&A events using mean residual data are discussed in Section 4.1. The results of the DiD analysis are presented in Section 4.2.

Table 4.1 **Input Data to Difference-in-Differences Model**

Category	**Company Data**	**Executive Data**
Control Acquirer	390	812
Control Acquired	342	433
Treatment Acquirer	330	431
Treatment Acquired	304	222
Total	**1,366**	**1,898**

4.1 Activities Around M&As

We derived the residual time series for daily engagement, cumulative followers, and cumulative statuses around M&A events for each company and executive entry to investigate the overall impact of M&A events on X activity. We calculated the mean residuals across the entire dataset for each time point of 241 days long time series and plotted them for the treatment and control groups as shown in Figure 4.1.

The impact of the M&A events on the residuals (deviations from the estimated trend) of X activity and engagement is more noticeable for companies (Figure 4.1a-c) compared to executives (Figure 4.1d-f). A greater increase in the number of statuses after the event indicates that companies tend to tweet more frequently following the announcement compared to the executives. Since M&A deal announcements typically include the company's name, it is expected that accounts with those names receive more followers and higher daily engagement than the executives associated with the companies.

Among the three types of metrics (followers, statuses, and daily engagement), the number of followers captures the most permanent impact of the M&A event, although statuses and daily engagement also show short-term effects (Figure 4.1a,d). Tweeting about the M&A or becoming more active on the account after the event would naturally lead to an increase in the number of statuses (Figure 4.1b,e), while daily engagement may rise accordingly (Figure 4.1c,f), as more tweets typically result in higher engagement. The lasting impact on followers is also expected, as M&A events attract public attention to the company and permanently increase its visibility.

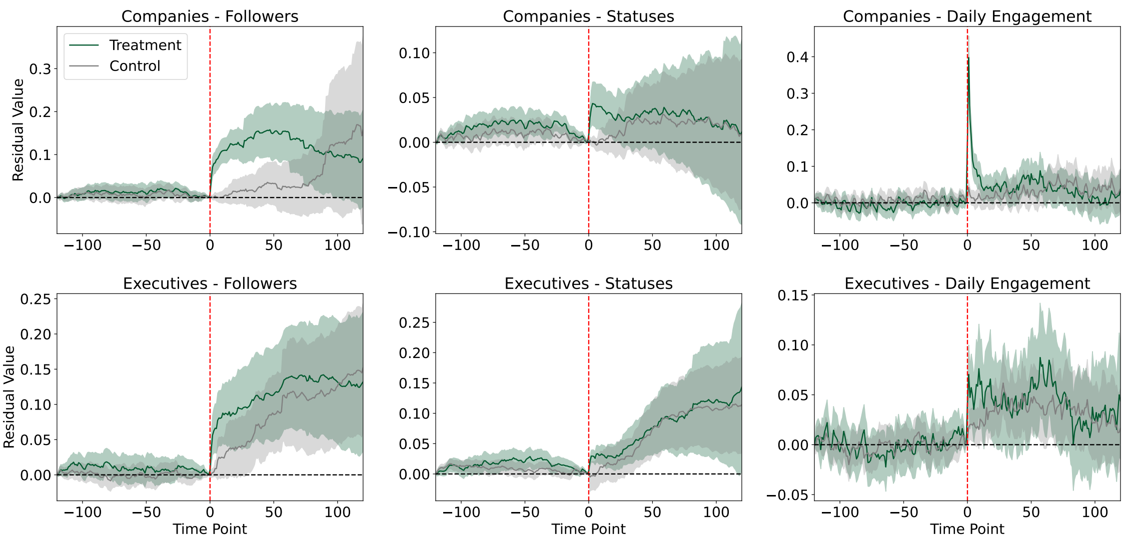

Figure 4.1 **Treatment Effect**. Mean residuals of change in followers, statuses and daily engagement time series of companies (a, b, c) and executives (d, e, f) demonstrating the difference between treatment and control groups following the event date.

4.2 Quantifying Treatment Effect

This section presents the results of the difference-in-differences (DiD) model described in Section 3.4. The results for companies and executives are reported separately in Sections 4.2.1 and 4.2.2, acquirer and target groups within the treatment and control datasets are distinguished in the analysis.

The linear regression model's target variable, y_h, represents the number of followers, statuses, or daily engagement at a given time point h. To capture the changing effect of the intervention over time, we utilized multiple post-event time frames as different experimental settings. We also conducted additional robustness checks using different pre- and post-event windows, alternative feature sets, and y_h values other than residuals, such as week-over-week differences that also illustrate the treatment effect. All robustness checks and supplementary results are provided in the Appendix.

The presented results in Figure 4.2 and Figure 4.3 illustrate the statistical significance of treatment coefficient β, dummy coefficient γ and interaction coefficient ρ in different experiments. A statistically significant and higher magnitude of ρ suggests that the event had a substantial impact on the treatment group, resulting in a notable difference compared to the control group. The interpretations of these coefficients are detailed in Section 3.4.

4.2.1 Companies

The DiD model results using the data of target companies show a significant ρ for followers and daily engagement, as illustrated in Figure 4.2d, and Figure 4.2e. However, the impact of the event on the statuses of target companies is more obscure (Figure 4.2e). Meanwhile, Figure 4.2a and Figure 4.2c highlight a notable increase in the followers, statuses and daily engagement of acquirer companies following the event.

Statistically significant ρ values in Figure 4.2a and Figure 4.2d indicate that the number of followers is notably influenced by M&A events for both acquirer and target companies. Specifically, acquirer company accounts begin to gain followers shortly after the event, with the effect intensifying over time and peaking around the 30th day following the announcement, then gradually declining in the long term. A

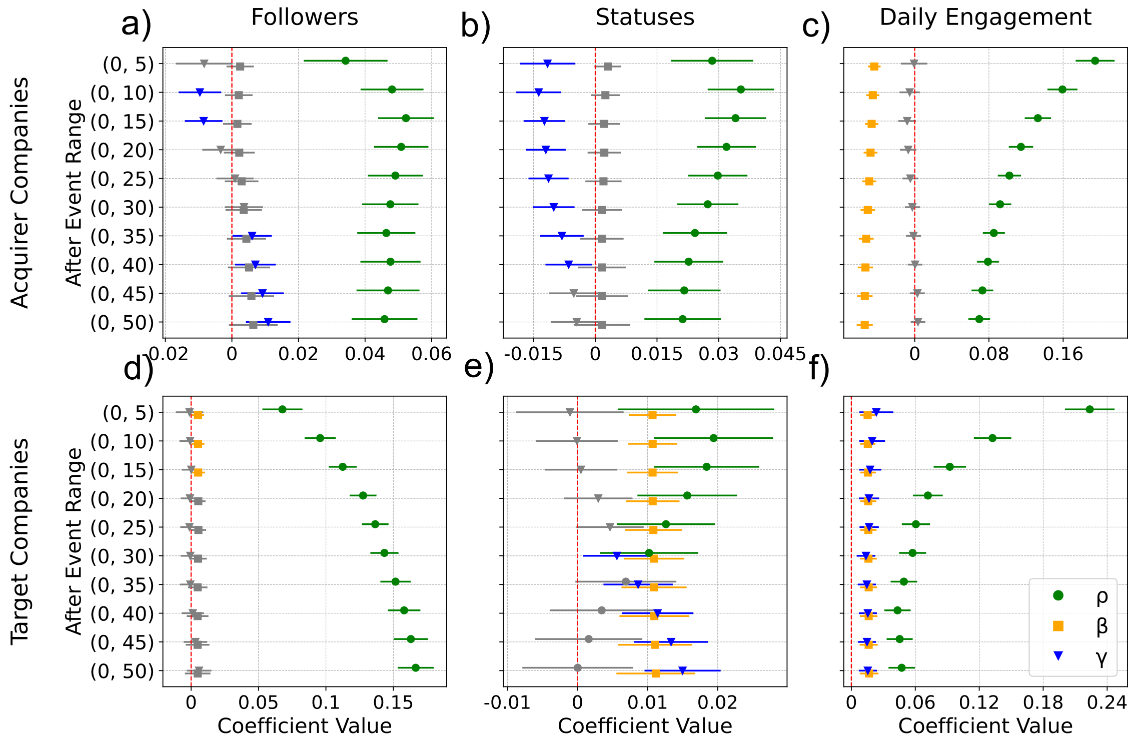

Figure 4.2 **Model Results - Companies** Diff-in-diff model results in terms of coefficient significance of β, γ and ρ. Statistically significant values of coefficients are shown colored and statistically insignificant values are all shown in gray. Before event range is constant and (-50, 0) for all experiments. Results for acquirer (a, b, c) and target (d, e, f) companies are shown in two rows.

similar but higher in magnitude effect persist longer for target companies, peaking around 85th day and start its gradual decline afterwards. This comparison demonstrates that the follower count of target companies following the M&A announcement experience a relatively higher increase in a longer term.

Figure 4.2a and 4.2e shows a gradual increase in γ over time. Recall that the residual represents the deviation from the expected trend, which is based on data prior to the event. Therefore, it is expected that the coefficient indicating the difference between the control time series before and after the event (γ) would increase over time as the residual is extrapolated beyond the event. A negative γ indicates that the control group exhibited a smaller-than-expected trend after the event. We observe that when it is negative, its change in magnitude over time is minimal while when it is positive, it increases more rapidly (Figure 4.2a). Since it is natural for the number of followers to grow over time, this trend may converge toward the expected values, resulting in γ showing little change in magnitude when its trend is on the negative side.

Positive and significant ρ values are observed in Figure 4.2b for the number of statuses of acquirer company accounts, although the effect is smaller in magnitude compared to that on followers. On the other hand, for target companies, no notable increase or decrease in the number of statuses can be related to the event (Figure 4.2e). Instances where the accounts of target companies stop tweeting or become inactive after the event may explain this situation.

The significant and negative β observed in Figure 4.2c suggests that the treatment accounts were gaining less public attention than the control accounts before the event. Conversely, the positive and significant β values in Figure 4.2e and Figure 4.2f indicate the opposite. While the matching process was optimized, we had already acknowledged that the pairings were not perfect. These statistically significant β values demonstrate that the matched treatment and control pairs for target and acquirer companies exhibit a statistically significant, yet negligible, difference in number of statuses.

The experiments done with daily engagement data, which reflects the received public attention, provides the strongest support for our claim, with statistically significant ρ peaking immediately after the event (Figure 4.2c and Figure 4.2f). The accounts of target companies attract a greater degree of public attention, while the effect diminishes over the next 100 days for both acquirer and target company accounts, as public engagement with their content gradually declines.

4.2.2 Executives

Experiments conducted with the executive data resulted in less significant ρ values compared to the company data, indicating weaker signals of the treatment effect on the executives' accounts.

Figure 4.3d shows an immediate increase in the followers of target executives, which continues to grow over the month following the event. Acquirer executives also gain followers right after the announcement in the first 5 days, though the effect is less permanent and smaller in magnitude (Figure 4.3a).

An instant and notable change in the number of statuses of acquirer executives after the event is seen although no significant change executives' status numbers, as indicated by the results in Figure 4.3b and Figure 4.3e.

On the other hand, a notable increase in public attention is evident for target executives following the event, as shown in Figure 4.3f. Although target executives do not tweet more frequently following the event (Figure 4.3e), the M&A announcement

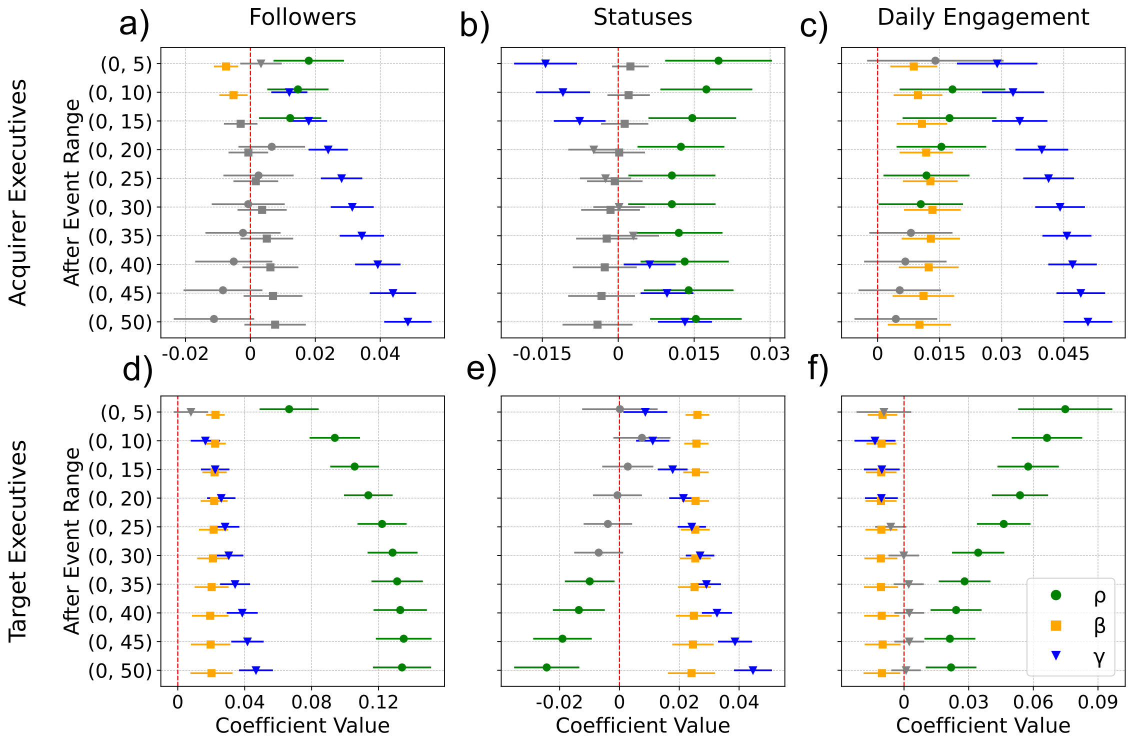

Figure 4.3 **Model Results - Executives** Diff-in-diff model results in terms of coefficient significance of β, γ and ρ. Statistically significant values of coefficients are shown colored and statistically insignificant values are all shown in gray. Before event range is constant and (-50, 0) for all experiments. Results for acquirer (a, b, c) and target (d, e, f) executives are shown in two rows.

seems to trigger public engagement with their accounts. Meanwhile, Figure 4.3c indicates that acquirer executives do not receive sufficient public attention after the event to suggest a significant difference from the gradual increase observed in the control group. Although ρ is statistically significant in some time ranges shown in Figure 4.3c, it is not substantial enough to confidently relate these changes to the event, as γ and β are also statistically significant and close in magnitude.

5. DISCUSSION & CONCLUSION

Our analysis of company and executive X account data around M&A event dates supports previous findings that X accounts and the activity levels of companies and executives play an important role in relation to financial events such as M&As.

Our findings suggest that the effect of M&A events is generally stronger on company accounts (Fig.4.2) than on executive accounts (Fig.4.3). This is likely because deal announcements are made in the name of the companies, naturally drawing more public attention to the company accounts, whereas the executives are not as visible or well-known.

Additionally, we observe that the accounts of target companies are more affected by M&A events compared to those of acquirer companies, with the impact being most evident in the follower count (Fig.4.2d) and daily engagement. Meanwhile, they do not seem to start tweeting more. This suggests that the increased public attention target companies gained is more related to the announcement itself rather than the content they share or an increasing activity on their account. Unlike target company accounts, acquirer companies demonstrate a significant change in their X activity in terms of number of statuses following the event.

Earlier studies have shown that large acquirer companies and their executives tend to use X actively Mazboudi & Khalil (2017); Wang et al. (2021). Given that acquirer companies are typically active on X, with higher follower and daily engagement numbers, it is unsurprising that M&A events have a smaller impact on their overall trends compared to those on the target companies. For instance, tripadvisor has a large X account, making it highly visible to the public. Thus, tripadvisor gains and loses followers and engagement not only due to financial events but also from non-financial activities or even a usual Tweet (see Figures 3.2 and 3.5). Large companies frequently take place in acquisitions and are known for much more than just their financial moves. A smaller target company on the other hand, may gain visibility for the first time through its involvement in a deal, leading to a much clearer effect on its accounts.

Another observation is that executives of target companies receive a significant amount of public attention (Fig.4.3d and Fig.4.3f). This may be due to the fact that target companies are the less known party before the deals and their name is heard with the M&A announcement, which increases their visibility compared to the executives of acquirer companies (Fig.4.3c). Among the experiments involving executives, follower and the daily engagement counts of acquirer executives show the most pronounced effect. On the other hand, number of statuses in acquirer executive accounts demonstrate a notable increase, in-line with the findings of acquirer companies.

Although some experiment groups yielded statistically insignificant results, our main findings confirm that M&A events impact the X activity and engagement of the companies and executives involved.

Our limitations include the lack of data on the duration of executives' tenure at the companies, which could result in cases where some executives were not present at the company during the M&A event. If the number of such cases is higher than anticipated, it may have led to an underestimation of the results' significance for executives. Another issue was that features like *employee count* for companies and *title* or *degree type* for executives are of the date Crunchbase entry was last updated. However, for instance, if an M&A deal happened in 2015 but the entry was of the date 2019, it is highly possible that the features were different (e.g. employee count was 50-100 instead of 1000-5000) back then. Considering this, employee count was not included in the matching features (see Section 3.3). While analyzing the Crunchbase records, we realized that some companies had the same Twitter url. We investigated these cases and found out that Crunchbase database updated the Twitter account of some target companies as the Twitter account of their acquirer. By manually checking these $\sim$500 entries where a Twitter url is duplicated in the dataset, we excluded the target companies with their acquirer's account information.

X has become a platform where financial events are frequently discussed and even influenced. In this paper, we demonstrate that the X accounts of companies and executives are affected by announced M&A deals. Specifically, the most statistically significant results are observed for followers of target and acquirer companies, statuses of target companies, daily engagement of both acquirer and target companies, as well as the followers of target executives and the daily engagement of acquirer executives. The approach we used can be adapted to investigate the effects of other types of financial events.

As major financial events involving acquirer and target companies, Mergers and acquisitions (MA) concern a diverse range of stakeholders. In this study, we examined the X activities of two key stakeholder groups—companies and executives involved in the deal—following MA announcements. Leveraging the growing power of social media data for event analysis, we also utilized financial data of Crunchbase and Thomson Reuters' The Securities Data Company. To the best of our knowledge, this is the first study to comprehensively explore the effects of M&A events on the X activity and public engagement of target and acquirer companies, along with their executives. Using a difference-in-differences methodology, we quantified the impact of these events on followers, statuses, and daily engagement metrics. Our findings revealed a significant shift in the followers and daily engagement of target and acquirer companies, with acquirer companies also showing a notable rise in status counts. While executive accounts were less affected by MA announcements, we observed significant changes in the status activity of acquirer executives and the follower and engagement metrics of target executives. This study not only provides a comparative analysis of how M&A events influence social media dynamics across different stakeholder groups (target vs. acquirer, company vs. executive) but also contributes to the literature by demonstrating the applicability of causal inference methodologies in multidisciplinary research encompassing financial events and social media data.

6. ROBUSTNESS EXPERIMENT RESULTS

In this section, we present robustness analyses of different difference-in-differences (DiD) experimental results that were not included in the main findings. More detailed results of robustness experiments may be found in Appendix B.

For the main results, we used residual time series for followers, statuses, and daily engagement data (see Section 3.2.5). The experiments were conducted on a fixed time series segment, starting 50 days before the event and extending across various segments up to 50 days after the event, to evaluate the lasting impact of the intervention. To test the robustness of our findings, additional experiments were conducted under two different scenarios, (i) using different before and after time ranges while maintaining residual time series as the raw data, (ii) using 7-day-difference time series instead of residuals while preserving the same time series segments as in the main analysis.

Figures 6.1 and 6.2 illustrate the results for extended post-event time ranges, up to 100 days after the event, while keeping the pre-event range fixed at $(-50, 0)$. These figures reveal how the coefficient ρ, representing the effect of the intervention, gradually decreases over time in cases where it was notably significant compared to other coefficients.

Interestingly, there are also instances where the magnitude of ρ increases. This behavior can be attributed to the nature of the expected trendline created using the values before the event, which forms the basis for generating residual time series. The trendline is less effective at extrapolating further values beyond the observed range, leading to discrepancies in the residuals. This limitation highlights why it was more reliable to focus on shorter post-event ranges in the analysis.

An additional analysis with an extended pre-event range $(-100, 0)$ showed similar significance levels for coefficients compared to the main results, but with slightly lower magnitudes. Notably, the shorter pre-event range $(-50, 0)$ yielded higher-magnitude coefficients with significant results, indicating that it is unnecessary to extend the range 100 days prior to the event to capture long-term effects (see Figures

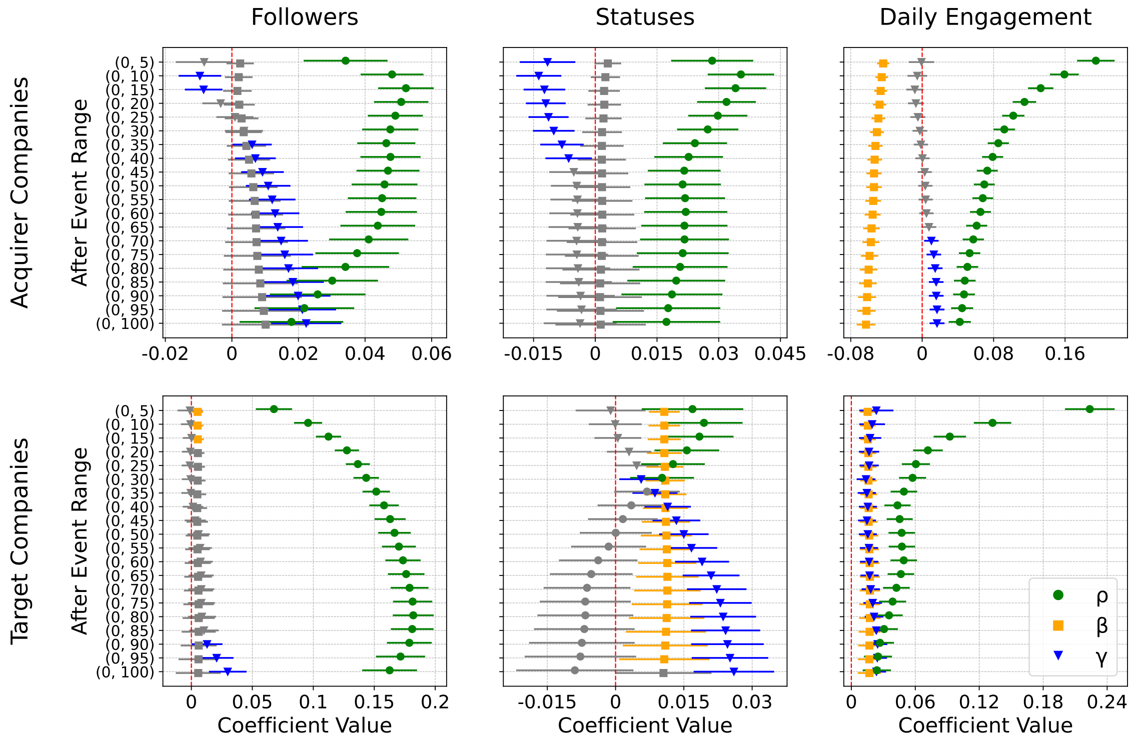

Figure 6.1 **Model Results - Different Time Frames Robustness Analysis for Companies** Diff-in-diff model results for companies with different time ranges than presented in the main results (Figure 4.2). Before time range is constant and (-50, 0) for all experiments. After time range for longer time periods (up to (0, 100) is shown in order to see the long-term effect.

6.3 and 6.4).

Experiments conducted on symmetric time ranges before and after the event, as shown in Figures 6.5 and 6.6, generally produced less significant results.

In addition to residuals, we constructed alternative time series for followers, statuses, and daily engagement by calculating (i) differences between each time point and the value 7 days prior, (ii) differences from the mean of the previous 7 days. These time series captured week-to-week changes and average deviations over the last week. The DiD experiments conducted on these alternative time series also demonstrated significant results, as shown in Figures 6.7 and 6.8.

(6.1)

$$y_h = \alpha + \beta_h T_h + \gamma_{h1} D_{h1} + \gamma_{h2} D_{h2} + \gamma_{h3} D_{h3} + \rho_{h1} T_h D_{h1} + \rho_{h2} T_h D_{h2} + \rho_{h3} T_h D_{h3} + \sum_{t=0}^{k} \sigma_t z_t$$

A modified difference-in-differences design (Equation 6.1) was employed to examine how the event's effect changes over time (Figure 6.9). The post-event time range was

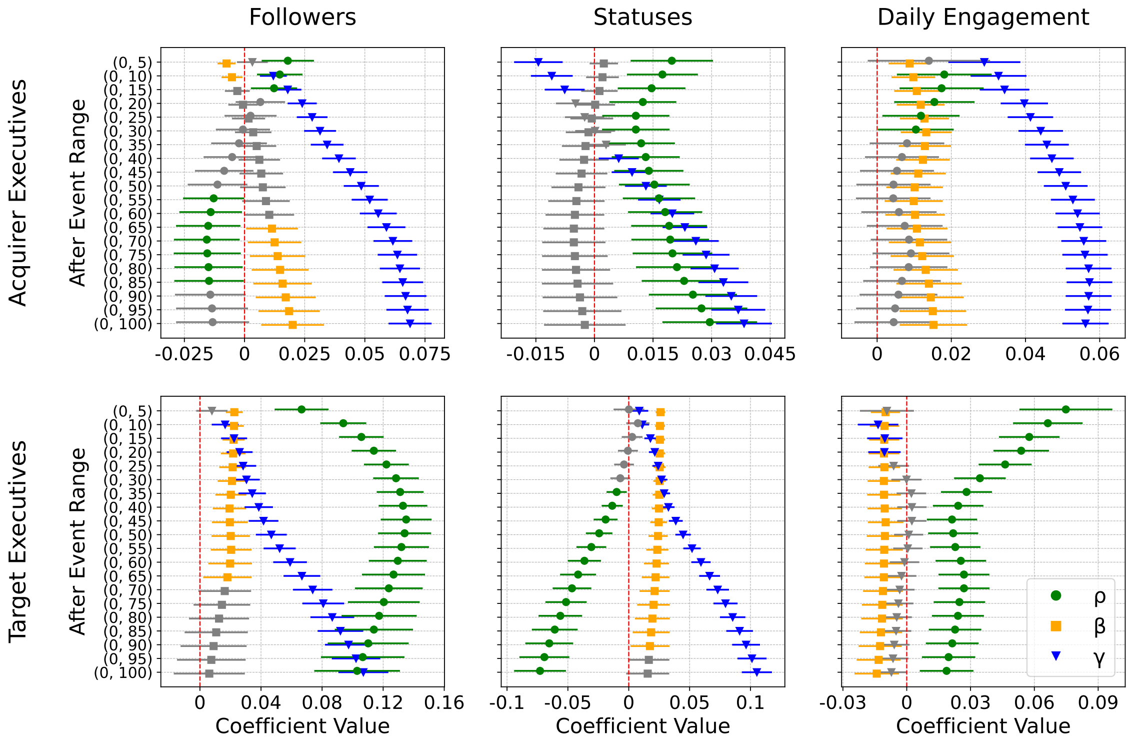

Figure 6.2 **Model Results - Different Time Frames Robustness Analysis for Executives** Diff-in-diff model results for executives with different time ranges than presented in the main results (Figure 4.3). Before time range is constant and (-50, 0) for all experiments. After time range for longer time periods (up to (0, 100) is shown in order to see the long-term effect.

divided into three distinct segments, with each segment represented by a separate D variable to indicate the time point's segment membership. Consequently, the equation incorporated three distinct γ, three interaction terms, and three corresponding ρ coefficients. The significance of these ρ coefficients illustrates the magnitude of the event's effect within each segment. Two pre-event time ranges $(-50, 0)$ and $(-90, 0)$ were paired with three post-event time ranges $(0, 90)$, $(0, 60)$, and $(0, 30)$ to conduct the analysis. The post-event periods were further divided into three segments to enable this segmented analysis, as described above.

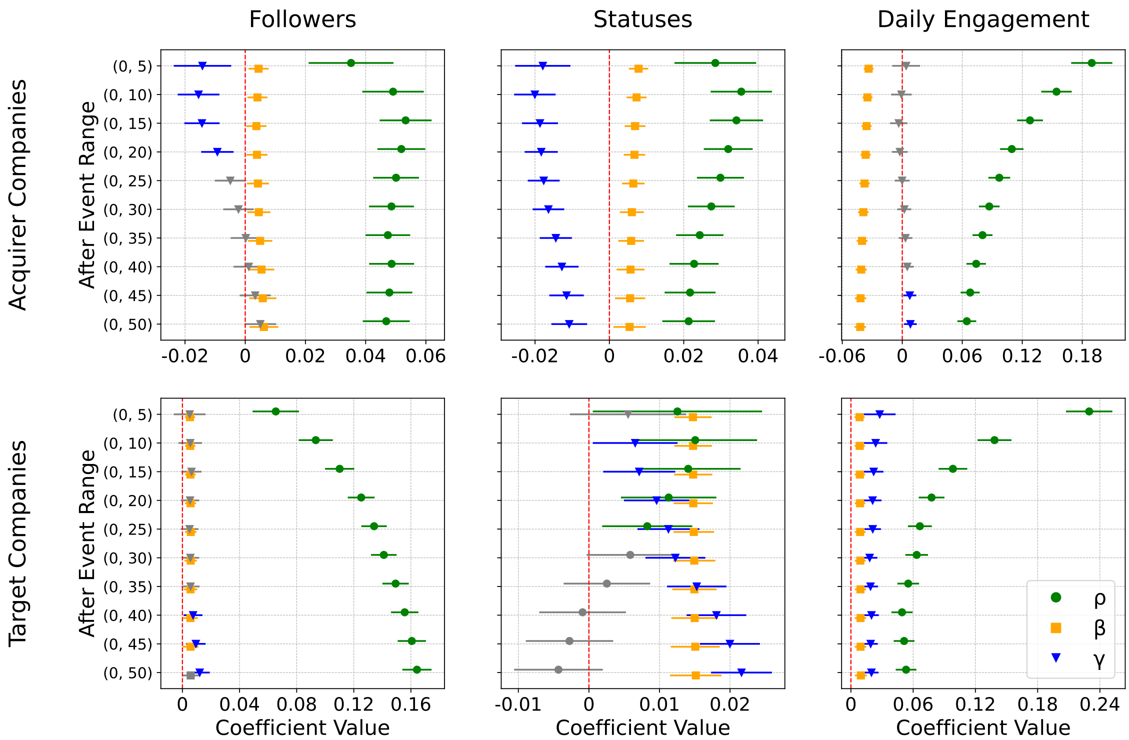

Figure 6.3 **Model Results - Different Time Frames Robustness Analysis for Companies** Diff-in-diff model results for companies with different time ranges than presented in the main results (Figure 4.2). Before time range being constant and (-100, 0), asymmetric after time ranges are used to see the the effect in time.

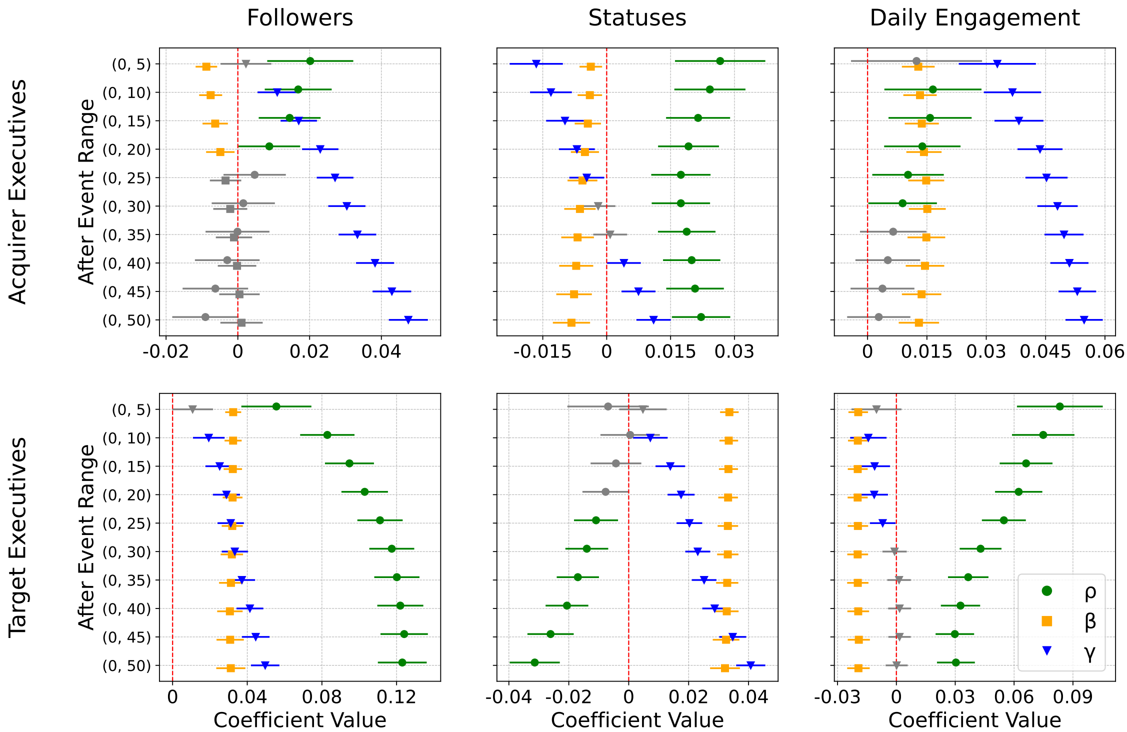

Figure 6.4 **Model Results - Different Time Frames Robustness Analysis for Executives** Diff-in-diff model results for executives with different time ranges than presented in the main results (Figure 4.3). Before time range being constant and (-100, 0), asymmetric after time ranges are used to see the the effect in time.

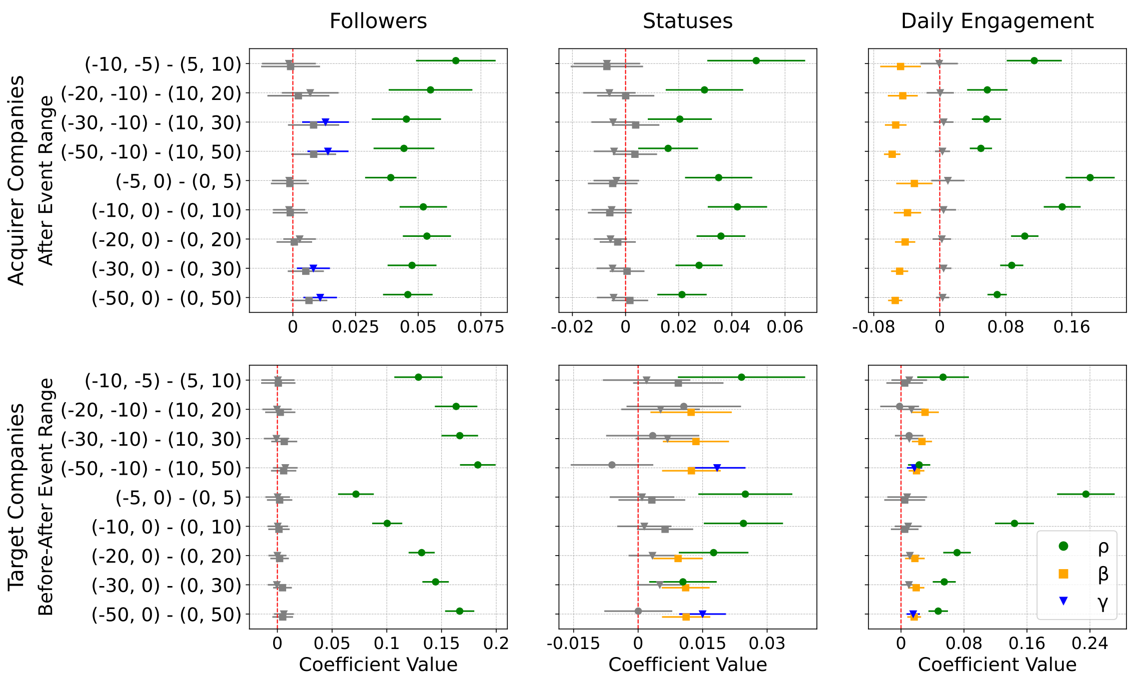

Figure 6.5 **Model Results - Different Time Frames Robustness Analysis for Companies** Diff-in-diff model results for companies with different time ranges than presented in the main results (Figure 4.2). Symmetric before and after time ranges are used to see the the effect of short and long time periods.

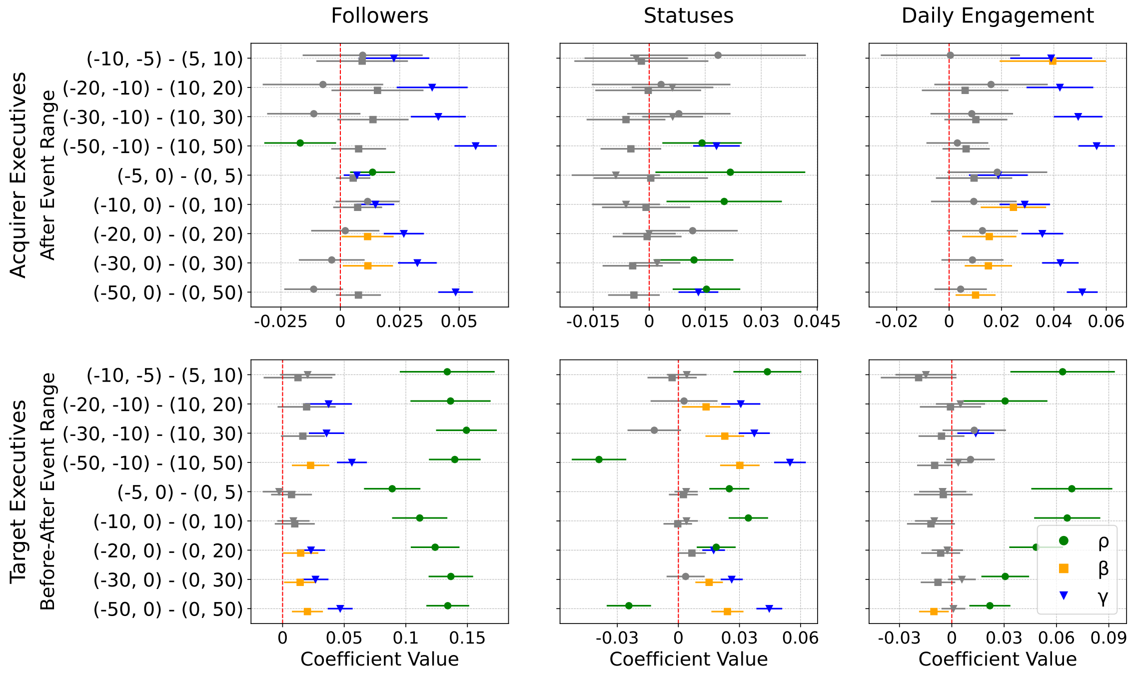

Figure 6.6 **Model Results - Different Time Frames Robustness Analysis for Executives** Diff-in-diff model results for executives with different time ranges than presented in the main results (Figure 4.3). Symmetric before and after time ranges are used to see the the effect of short and long time periods.

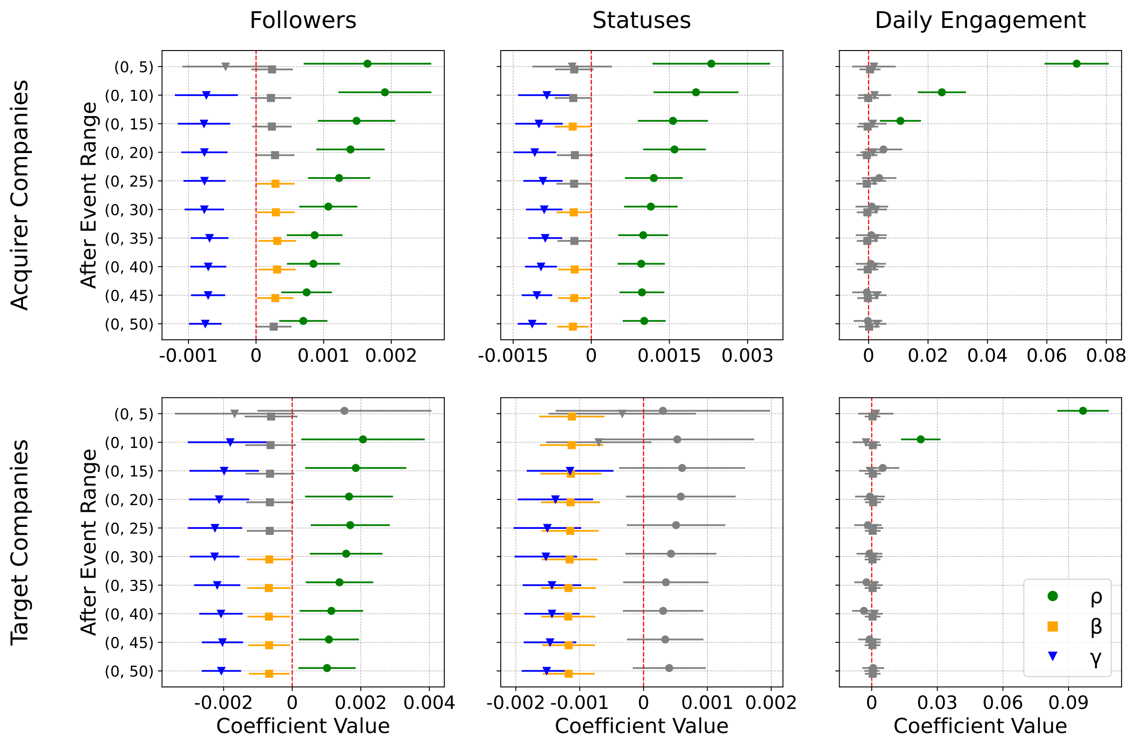

Figure 6.7 **Model Results - Different Time Series Values Robustness Analysis for Companies** Diff-in-diff model results for companies with different time series values unlike residuals used in the main results (Figure 4.2). Every time point is the difference of the normalized value from the 7 day before.

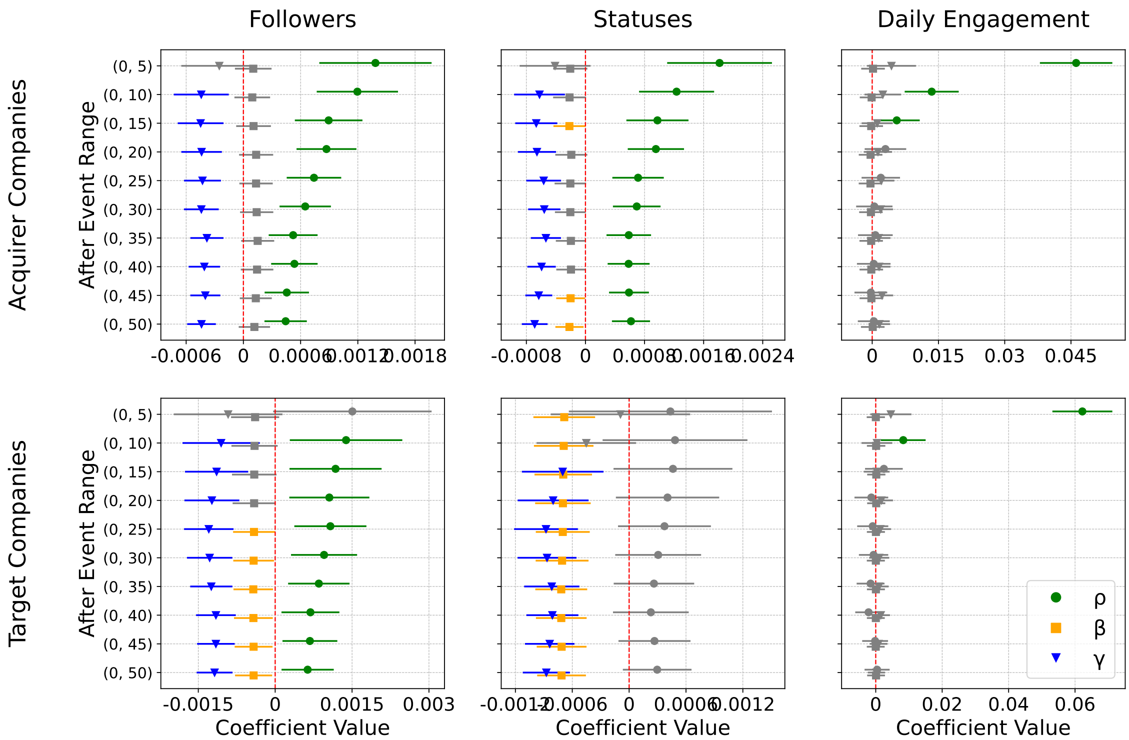

Figure 6.8 **Model Results - Different Time Series Values Robustness Analysis for Companies** Diff-in-diff model results for companies with different time series values unlike residuals used in the main results (Figure 4.2). Every time point is the difference of the normalized value from the mean of the last 7 days.

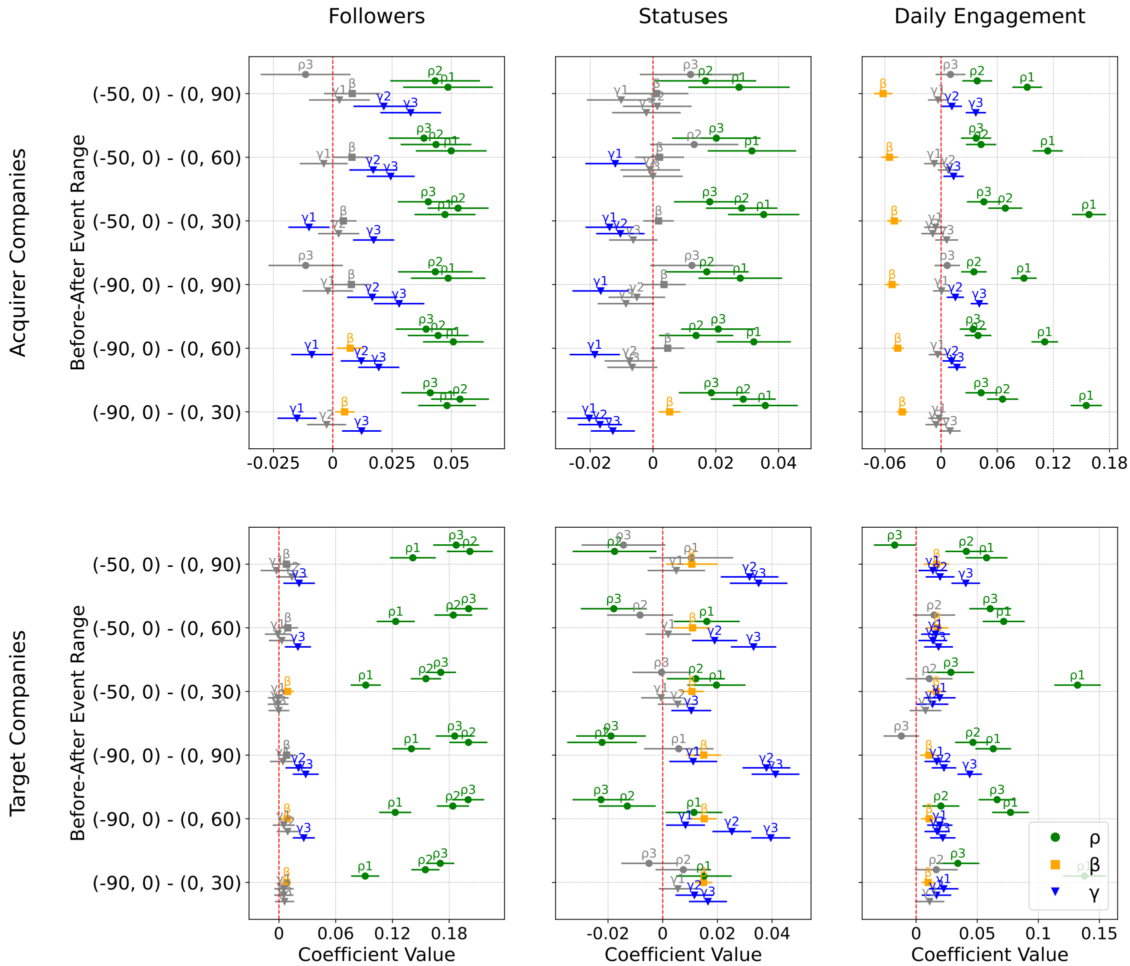

Figure 6.9 **Model Results - Multiple Rho - Robustness Analysis for Companies** Diff-in-diff model results for companies with different time ranges and additional features, namely multiple rhos and gammas for segregated time ranges after the event to how the effect's significance change over time.

BIBLIOGRAPHY

Ahern, K. R., Daminelli, D., & Fracassi, C. (2015). Lost in translation? the effect of cultural values on mergers around the world. *Journal of Financial Economics*, *117*(1), 165–189. NBER Conference on the Causes and Consequences of Corporate Culture.

Alsaedi, N. & Burnap, P. (2015). Feature extraction and analysis for identifying disruptive events from social media. In *Proceedings of the 2015 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining 2015*, (pp. 1495–1502).

Ansah, J., Liu, L., Kang, W., Liu, J., & Li, J. (2020). Leveraging burst in twitter network communities for event detection. *World Wide Web*, *23*, 2851–2876.

Batrinca, B. & Treleaven, P. C. (2015). Social media analytics: a survey of techniques, tools and platforms. *Ai & Society*, *30*, 89–116.

Behrendt, S. & Schmidt, A. (2018). The twitter myth revisited: Intraday investor sentiment, twitter activity and individual-level stock return volatility. *Journal of Banking and Finance*, *96*, 355–367.

Blankespoor, E., Miller, G. S., & White, H. D. (2014). The role of dissemination in market liquidity: Evidence from firms' use of twitter™. *The accounting review*, *89*(1), 79–112.

Braghieri, L., Levy, R., & Makarin, A. (2022). Social media and mental health. *American Economic Review*, *112*(11), 3660–93.

Branas, C. C., Cheney, R. A., MacDonald, J. M., Tam, V. W., Jackson, T. D., & Ten Have, T. R. (2011). A difference-in-differences analysis of health, safety, and greening vacant urban space. *American journal of epidemiology*, *174*(11), 1296–1306.

Broersma, M. & Graham, T. (2013). Twitter as a news source: How dutch and british newspapers used tweets in their news coverage, 2007–2011. *Journalism practice*, *7*(4), 446–464.

Cartwright, S. & Cooper, C. L. (2018). The psychological impact of merger and acquisition on the individual: A study of building society managers. In *Managerial, Occupational and Organizational Stress Research* (pp. 429–450). Routledge.

Chen, W., Liu, Y., Liu, S., Chen, Y., & Zhang, P. (2024). The governance effects of social media engagement on ma outcomes: Evidence from china. *Journal of International Financial Markets, Institutions and Money*, *91*, 101946.

Cookson, J. A., Niessner, M., & Schiller, C. (2022). Can social media inform corporate decisions? evidence from merger withdrawals. Technical report, Center for Open Science.

Dang, S. (2023). Elon musk's x restructuring curtails disinformation research, spurs legal fears. Accessed: 2023-11-17.

Deng, W., Xu, N., Li, H., Liu, F., & Shi, Y. (2019). Difference in differences in marketing performance measurement. *Procedia Computer Science*, *162*, 275–280.

DePamphilis, D. (2021). *Mergers, acquisitions, and other restructuring activities: An integrated approach to process, tools, cases, and solutions*. Academic Press.

Derrien, F. & Kecskés, A. (2013). The real effects of financial shocks: Evidence from exogenous changes in analyst coverage. *The Journal of Finance*, *68*(4), 1407–1440.

Ershov, D. & Mitchell, M. (2020). The effects of influencer advertising disclosure regulations: Evidence from instagram. In *Proceedings of the 21st ACM Conference on Economics and Computation*, EC '20, (pp. 73–74)., New York, NY, USA. Association for Computing Machinery.

Fan, R., Talavera, O., & Tran, V. (2020). Social media bots and stock markets. *European Financial Management*, *26*, 753–777.

Gaughan, P. A. (2015). *Mergers, Acquisitions, and Corporate Restructurings*. John Wiley & Sons, Incorporated.

Goodman-Bacon, A. & Marcus, J. (2020). Using difference-in-differences to identify causal effects of covid-19 policies.

Hanushek, E. A. & W ößmann, L. (2006). Does educational tracking affect performance and inequality? differences-in-differences evidence across countries. *The Economic Journal*, *116*(510), C63–C76.

Hollebeek, L. D., Glynn, M. S., & Brodie, R. J. (2014). Consumer brand engagement in social media: Conceptualization, scale development and validation. *Journal of interactive marketing*, *28*(2), 149–165.

Horta Ribeiro, M., Hosseinmardi, H., West, R., & Watts, D. J. (2023). Deplatforming did not decrease parler users' activity on fringe social media. *PNAS nexus*, *2*(3), pgad035.

Hsu, J. T.-H. & Tsai, R. T.-H. (2022). Increased online aggression during covid-19 lockdowns: Two-stage study of deep text mining and difference-in-differences analysis. *J Med Internet Res*, *24*(8), e38776.

Jayasuriya, D. & O'Neill, B. (2021). Social media's impact on the global mergers and acquisitions market. *Journal of Risk and Financial Management*, *14*(4), 157.

Jia, W., Redigolo, G., Shu, S., & Zhao, J. (2020). Can social media distort price discovery? evidence from merger rumors. *Journal of Accounting and Economics*, *70*(1), 101334.

Karami, A., Lundy, M., Webb, F., & Dwivedi, Y. K. (2020). Twitter and research: A systematic literature review through text mining. *IEEE access*, *8*, 67698–67717.

Kassens-Noor, E., Vertalka, J., & Wilson, M. (2019). Good games, bad host? using big data to measure public attention and imagery of the olympic games. *Cities*, *90*, 229–236.

Kim, J. W., Kim, D., Keegan, B., Kim, J. H., Kim, S., & Oh, A. (2015). Social media dynamics of global co-presence during the 2014 fifa world cup. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, (pp. 2623–2632).

Kuhn, H. W. (1955). The hungarian method for the assignment problem. *Naval Research Logistics Quarterly*, *2*(1-2), 83–97.

Levi, M., Li, K., & Zhang, F. (2014). Director gender and mergers and acquisitions. *Journal of Corporate Finance*, *28*, 185–200.

Li, Z. F., Liang, C. Y., & Tang, Z. (2024). Ceo social media presence and insider trading behavior. *Available at SSRN 3532495*.

Lin, C. Y.-Y. & Wei, Y.-C. (2006). The role of business ethics in merger and acquisition success: An empirical study. *Journal of Business Ethics*, *69*, 95–109.

Mazboudi, M. & Khalil, S. (2017). The attenuation effect of social media: Evidence from acquisitions by large firms. *Journal of Financial Stability*, *28*, 115–124.

Najafi, A., Mugurtay, N., Zouzou, Y., Demirci, E., Demirkiran, S., Karadeniz, H. A., & Varol, O. (2024). First public dataset to study 2023 turkish general election. *Scientific Reports*, *14*(1), 8794.

Phan, T. Q. & Airoldi, E. M. (2015). A natural experiment of social network formation and dynamics. *Proceedings of the National Academy of Sciences*, *112*(21), 6595–6600.

Piesse, J., Lee, C.-F., Lin, L., & Kuo, H.-C. (2022). Merger and acquisition: Definitions, motives, and market responses. In *Encyclopedia of finance* (pp. 877–894). Springer.

Pourebrahim, N., Sultana, S., Edwards, J., Gochanour, A., & Mohanty, S. (2019). Understanding communication dynamics on twitter during natural disasters: A case study of hurricane sandy. *International journal of disaster risk reduction*, *37*, 101176.

Qu, Y., Huang, C., Zhang, P., & Zhang, J. (2011). Microblogging after a major disaster in china: a case study of the 2010 yushu earthquake. In *Proceedings of the ACM 2011 conference on Computer supported cooperative work*, (pp.

25–34).

Rietveld, R., Van Dolen, W., Mazloom, M., & Worring, M. (2020). What you feel, is what you like influence of message appeals on customer engagement on instagram. *Journal of Interactive Marketing*, *49*(1), 20–53.

Sakaki, T., Okazaki, M., & Matsuo, Y. (2010). Earthquake shakes twitter users: real-time event detection by social sensors. In *Proceedings of the 19th international conference on World wide web*, (pp. 851–860).

Schiozer, R. F., Mourad, F. A., & Martins, T. C. (2020). A tutorial on the use of differences-in-differences in management, finance, and accounting. *Revista de Administração Contemporânea*, *25*, e200067.

Schuler, R. & Jackson, S. (2017). Hr issues and activities in mergers and acquisitions. In *International Human Resource Management* (pp. 445–458). Routledge.

Seo, M.-G. & Hill, N. S. (2005). Understanding the human side of merger and acquisition: An integrative framework. *The Journal of Applied Behavioral Science*, *41*(4), 422–443.

Sismeiro, C. & Mahmood, A. (2018). Competitive vs. complementary effects in online social networks and news consumption: A natural experiment. *Management Science*, *64*(11), 5014–5037.

Slaughter, M. J. (2001). Trade liberalization and per capita income convergence: a difference-in-differences analysis. *Journal of International Economics*, *55*(1), 203–228.

Starbird, K., Maddock, J., Orand, M., Achterman, P., & Mason, R. M. (2014). Rumors, false flags, and digital vigilantes: Misinformation on twitter after the 2013 boston marathon bombing. *IConference 2014 proceedings*.

Varol, O. (2023). Should we agree to disagree about twitter's bot problem? *Online Social Networks and Media*, *37*, 100263.

Varol, O., Ferrara, E., Ogan, C. L., Menczer, F., & Flammini, A. (2014). Evolution of online user behavior during a social upheaval. In *Proceedings of the 2014 ACM conference on Web science*, (pp. 81–90).

Vieweg, S., Hughes, A. L., Starbird, K., & Palen, L. (2010). Microblogging during two natural hazards events: what twitter may contribute to situational awareness. In *Proceedings of the SIGCHI conference on human factors in computing systems*, (pp. 1079–1088).

Wallach, K. (2014). A content analysis of twitter use: factors that might increase music sales during an award show. *Elon Journal of Undergraduate Research in Communications*, *5*(1).

Wang, Q. & Lau, R. (2019). The impact of investors' surprise emotion on post-m&a performance: A social media analytics approach.

Wang, Q., Lau, R. Y. K., & Xie, H. (2021). The impact of social executives on firms' mergers and acquisitions strategies: A difference-in-differences analysis. *Journal of Business Research*, *123*, 343–354.

Yang, T. & Peng, Y. (2022). The importance of trending topics in the gatekeeping of social media news engagement: A natural experiment on weibo. *Communication Research*, *49*(7), 994–1015.

Zhu, Y., Cao, L., Xie, J., Yu, Y., Chen, A., & Huang, F. (2023). Using social media data to assess the impact of covid-19 on mental health in china. *Psychological Medicine*, *53*(2), 388–395.

APPENDIX A

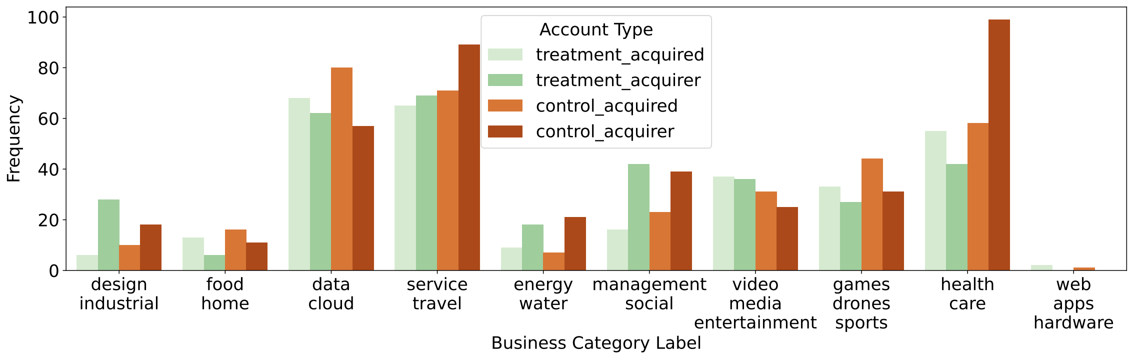

Figure A.1 **Business Category Distribution of Companies** Business category distribution among 1365 companies included in DiD analysis.

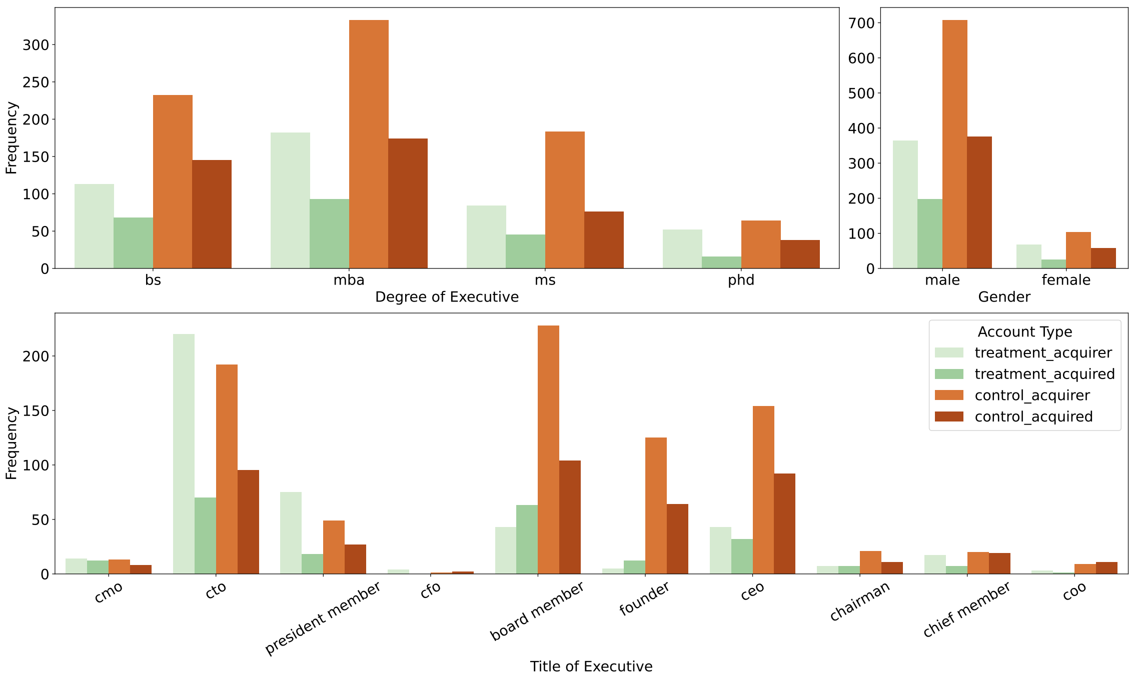

Figure A.2 **Distribution of Executive Features** Feature distribution among 1898 executives included in DiD analysis.

Original Title	**Operation**	**Final Title**
chief executive officer	replace	ceo
chief technology officer	replace	cto
chief operating officer	replace	coo
chief marketing officer	replace	cmo
chief financial officer	replace	cfo
chairman	contains	chairman
board	contains	board member
president	contains	president member
chief	contains	chief member
director	contains	director member
founder	contains	founder

Table A.1 Title Standardization for Executives

Original Degrees	**Final Degree**
bsc, bse, bsba, bsee, bachelor of science bs	bs
msc, mse, msee	ms
phd	phd
mba	mba

Table A.2 Degree Type Standardization for Executives Mapping

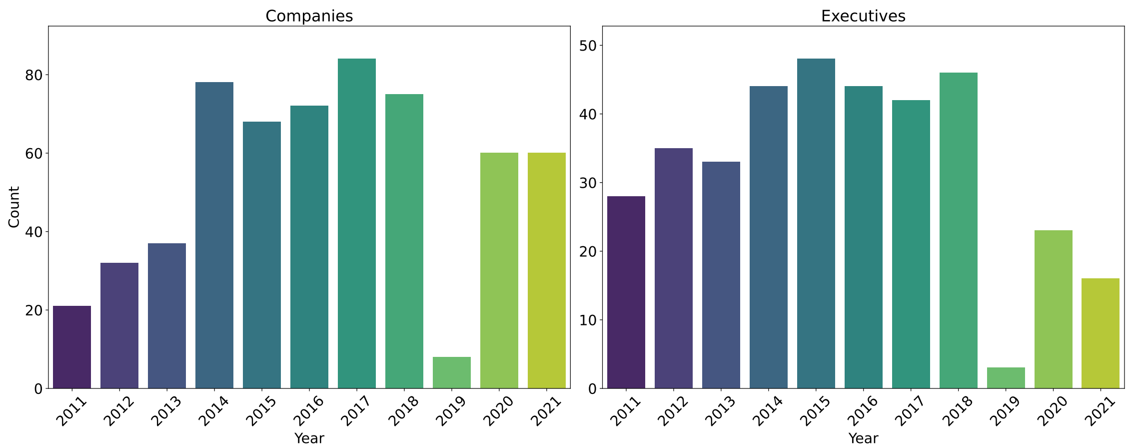

Figure A.3 **Distribution of Unique Deal Dates Across Years** Among unique deal dates of companies (595) and executives (362) in our data, most of the deals belong to the years before 2019.

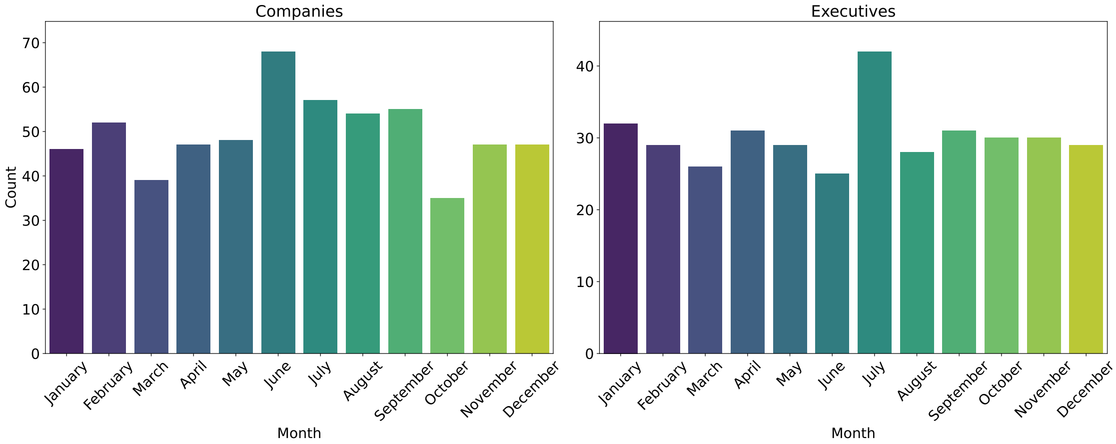

Figure A.4 **Distribution of Unique Deal Dates Across Months** Among unique deal dates of companies (595) and executives (362) in our data, there are no significant differences in the number of the deals announced in different months.

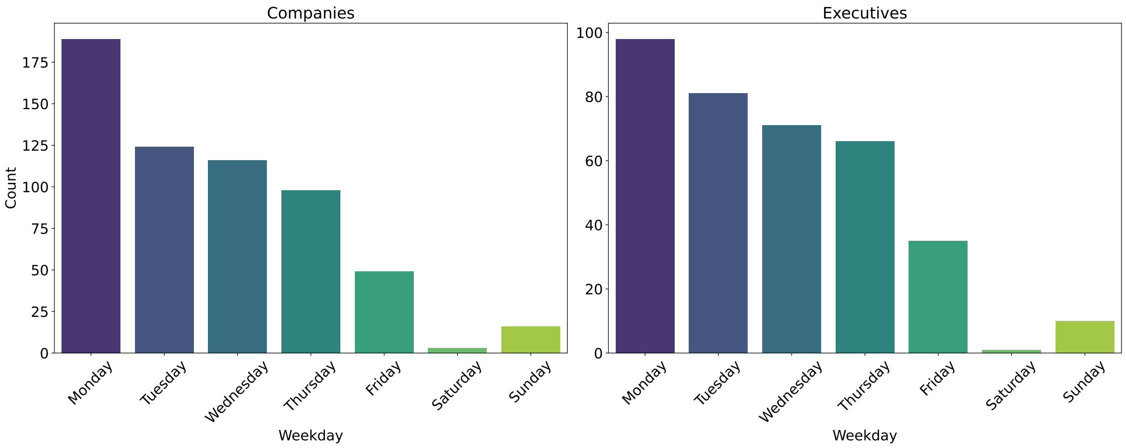

Figure A.5 **Distribution of Unique Deal Dates Across Weekdays** Among unique deal dates of companies (595) and executives (362) most of the deals were announced on Monday. Meanwhile very little of the deals were announced during the weekend.

APPENDIX B

Table B.1 **Companies - Followers** Robustness Analysis Results for Different Time Ranges with Before Event Range as (-100, 0)

Event Range		*Rho*		*Gamma*		*Beta*	
Before	After	Value	P-Value	Value	P-Value	Value	P-Value
(-100, 0)	(0, 5)	**0.0351**	0.0000	**-0.0142**	0.0035	**0.0044**	0.0092
(-100, 0)	(0, 10)	**0.0491**	4.30e-21	**-0.0155**	1.00e-05	**0.0041**	0.0167
(-100, 0)	(0, 15)	**0.0533**	1.20e-33	**-0.0144**	0.0000	**0.0037**	0.0307
(-100, 0)	(0, 20)	**0.0518**	2.30e-37	**-0.0092**	0.0008	**0.0039**	0.0282
(-100, 0)	(0, 25)	**0.0501**	4.80e-38	-0.0049	0.0600	**0.0042**	0.0234
(-100, 0)	(0, 30)	**0.0486**	2.60e-37	-0.0022	0.3830	**0.0045**	0.0208
(-100, 0)	(0, 35)	**0.0474**	6.90e-36	0.0002	0.9412	**0.0050**	0.0160
(-100, 0)	(0, 40)	**0.0486**	2.70e-37	0.0012	0.6477	**0.0054**	0.0126
(-100, 0)	(0, 45)	**0.0479**	7.50e-35	0.0033	0.2077	**0.0058**	0.0112
(-100, 0)	(0, 50)	**0.0468**	5.80e-32	0.0050	0.0623	**0.0062**	0.0112
(-100, 0)	(0, 55)	**0.0461**	1.40e-29	**0.0062**	0.0241	**0.0064**	0.0123
(-100, 0)	(0, 60)	**0.0459**	7.10e-28	**0.0071**	0.0122	**0.0066**	0.0146
(-100, 0)	(0, 65)	**0.0448**	5.90e-25	**0.0079**	0.0073	**0.0067**	0.0199
(-100, 0)	(0, 70)	**0.0421**	2.30e-20	**0.0089**	0.0038	**0.0068**	0.0272
(-100, 0)	(0, 75)	**0.0386**	4.60e-16	**0.0100**	0.0019	**0.0069**	0.0340
(-100, 0)	(0, 80)	**0.0351**	1.30e-12	**0.0111**	0.0009	**0.0073**	0.0364
(-100, 0)	(0, 85)	**0.0311**	0.0000	**0.0124**	0.0003	**0.0076**	0.0383
(-100, 0)	(0, 90)	**0.0268**	0.0000	**0.0140**	0.0001	**0.0080**	0.0390
(-100, 0)	(0, 95)	**0.0228**	4.00e-05	**0.0153**	5.00e-05	**0.0084**	0.0398
(-100, 0)	(0, 100)	**0.0189**	0.0011	**0.0164**	3.00e-05	**0.0088**	0.0396

Table B.2 **Companies - Statuses** Robustness Analysis Results for Different Time Ranges with Before Event Range as (-100, 0)

Event Range		*Rho*		*Gamma*		*Beta*	
Before	After	Value	P-Value	Value	P-Value	Value	P-Value
(-100, 0)	(0, 5)	**0.0285**	0.0000	**-0.0179**	0.0000	**0.0078**	0.0000
(-100, 0)	(0, 10)	**0.0355**	3.50e-17	**-0.0200**	2.00e-12	**0.0073**	0.0000
(-100, 0)	(0, 15)	**0.0342**	9.60e-21	**-0.0187**	4.80e-14	**0.0069**	0.0000
(-100, 0)	(0, 20)	**0.0320**	1.50e-21	**-0.0183**	7.00e-16	**0.0067**	0.0000
(-100, 0)	(0, 25)	**0.0299**	2.20e-20	**-0.0177**	6.50e-16	**0.0064**	3.00e-05
(-100, 0)	(0, 30)	**0.0274**	1.40e-17	**-0.0164**	4.70e-14	**0.0060**	0.0003
(-100, 0)	(0, 35)	**0.0243**	7.70e-14	**-0.0144**	6.00e-11	**0.0059**	0.0009
(-100, 0)	(0, 40)	**0.0228**	1.40e-11	**-0.0128**	0.0000	**0.0057**	0.0030
(-100, 0)	(0, 45)	**0.0217**	0.0000	**-0.0115**	0.0000	**0.0056**	0.0070
(-100, 0)	(0, 50)	**0.0213**	0.0000	**-0.0108**	1.00e-05	**0.0054**	0.0141
(-100, 0)	(0, 55)	**0.0219**	0.0000	**-0.0106**	3.00e-05	**0.0053**	0.0234
(-100, 0)	(0, 60)	**0.0221**	0.0000	**-0.0106**	5.00e-05	**0.0052**	0.0355
(-100, 0)	(0, 65)	**0.0217**	0.0000	**-0.0106**	8.00e-05	0.0051	0.0515
(-100, 0)	(0, 70)	**0.0218**	0.0000	**-0.0108**	8.00e-05	0.0050	0.0702
(-100, 0)	(0, 75)	**0.0213**	0.0000	**-0.0108**	0.0001	0.0048	0.0927
(-100, 0)	(0, 80)	**0.0207**	0.0000	**-0.0105**	0.0003	0.0046	0.1264
(-100, 0)	(0, 85)	**0.0198**	1.00e-05	**-0.0103**	0.0006	0.0044	0.1646
(-100, 0)	(0, 90)	**0.0187**	4.00e-05	**-0.0099**	0.0013	0.0043	0.1940
(-100, 0)	(0, 95)	**0.0178**	0.0001	**-0.0097**	0.0023	0.0043	0.2135
(-100, 0)	(0, 100)	**0.0174**	0.0003	**-0.0100**	0.0022	0.0042	0.2359

Table B.3 **Companies - Daily Engagement** Robustness Analysis Results for Different Time Ranges with Before Event Range as (-100, 0)

Event Range		*Rho*		*Gamma*		*Beta*	
Before	After	Value	P-Value	Value	P-Value	Value	P-Value
(-100, 0)	(0, 5)	**0.1895**	1.10e-72	0.0039	0.5829	**-0.0336**	1.30e-41
(-100, 0)	(0, 10)	**0.1542**	2.20e-87	-0.0008	0.8721	**-0.0348**	1.10e-42
(-100, 0)	(0, 15)	**0.1277**	4.80e-83	-0.0035	0.4304	**-0.0357**	1.20e-43
(-100, 0)	(0, 20)	**0.1095**	4.90e-75	-0.0024	0.5548	**-0.0366**	2.30e-44
(-100, 0)	(0, 25)	**0.0970**	4.10e-68	-0.0001	0.9732	**-0.0377**	2.70e-45
(-100, 0)	(0, 30)	**0.0870**	4.70e-61	0.0021	0.5634	**-0.0389**	9.70e-47
(-100, 0)	(0, 35)	**0.0803**	6.50e-56	0.0032	0.3504	**-0.0402**	7.60e-48
(-100, 0)	(0, 40)	**0.0739**	4.80e-50	0.0050	0.1358	**-0.0410**	1.10e-47
(-100, 0)	(0, 45)	**0.0679**	5.40e-44	**0.0075**	0.0230	**-0.0417**	2.70e-47
(-100, 0)	(0, 50)	**0.0645**	4.70e-41	**0.0081**	0.0124	**-0.0420**	3.60e-46
(-100, 0)	(0, 55)	**0.0629**	4.70e-40	**0.0086**	0.0078	**-0.0428**	2.00e-46
(-100, 0)	(0, 60)	**0.0603**	2.10e-37	**0.0094**	0.0031	**-0.0435**	4.60e-46
(-100, 0)	(0, 65)	**0.0560**	1.70e-32	**0.0123**	0.0001	**-0.0445**	5.10e-46
(-100, 0)	(0, 70)	**0.0522**	1.80e-28	**0.0150**	0.0000	**-0.0453**	1.00e-45
(-100, 0)	(0, 75)	**0.0481**	2.30e-24	**0.0177**	0.0000	**-0.0465**	2.30e-46
(-100, 0)	(0, 80)	**0.0457**	4.30e-22	**0.0192**	0.0000	**-0.0475**	1.10e-46
(-100, 0)	(0, 85)	**0.0427**	1.60e-19	**0.0203**	0.0000	**-0.0483**	9.20e-47
(-100, 0)	(0, 90)	**0.0418**	9.80e-19	**0.0204**	0.0000	**-0.0491**	6.40e-47
(-100, 0)	(0, 95)	**0.0397**	5.90e-17	**0.0213**	3.60e-11	**-0.0499**	7.70e-47
(-100, 0)	(0, 100)	**0.0371**	5.90e-15	**0.0213**	3.60e-11	**-0.0505**	9.80e-47

Table B.4 **Executives - Followers** Robustness Analysis Results for Different Time Ranges with Before Event Range as (-100, 0)

Event Range		*Rho*		*Gamma*		*Beta*	
Before	After	Value	P-Value	Value	P-Value	Value	P-Value
(-100, 0)	(0, 5)	**0.0202**	0.0010	0.0023	0.5306	**-0.0088**	0.0000
(-100, 0)	(0, 10)	**0.0168**	0.0004	**0.0110**	9.00e-05	**-0.0076**	0.0000
(-100, 0)	(0, 15)	**0.0144**	0.0010	**0.0170**	5.80e-11	**-0.0063**	0.0005
(-100, 0)	(0, 20)	**0.0088**	0.0456	**0.0230**	6.30e-19	**-0.0049**	0.0159
(-100, 0)	(0, 25)	0.0047	0.2902	**0.0271**	3.20e-25	-0.0034	0.1250
(-100, 0)	(0, 30)	0.0015	0.7349	**0.0304**	1.60e-30	-0.0021	0.3819
(-100, 0)	(0, 35)	-9.65e-05	0.9830	**0.0333**	1.30e-35	-0.0011	0.6781
(-100, 0)	(0, 40)	-0.0029	0.5219	**0.0382**	3.10e-45	-0.0002	0.9352
(-100, 0)	(0, 45)	-0.0063	0.1787	**0.0429**	3.60e-55	0.0005	0.8756
(-100, 0)	(0, 50)	-0.0090	0.0555	**0.0475**	1.50e-65	0.0010	0.7323
(-100, 0)	(0, 55)	**-0.0106**	0.0264	**0.0510**	7.20e-73	0.0021	0.5148
(-100, 0)	(0, 60)	**-0.0119**	0.0153	**0.0546**	8.60e-80	0.0031	0.3398
(-100, 0)	(0, 65)	**-0.0129**	0.0099	**0.0580**	3.50e-86	0.0041	0.2349
(-100, 0)	(0, 70)	**-0.0135**	0.0081	**0.0607**	6.10e-91	0.0050	0.1636
(-100, 0)	(0, 75)	**-0.0133**	0.0101	**0.0625**	1.80e-93	0.0060	0.1023
(-100, 0)	(0, 80)	**-0.0128**	0.0152	**0.0636**	1.30e-93	0.0069	0.0689
(-100, 0)	(0, 85)	**-0.0126**	0.0186	**0.0647**	3.60e-94	**0.0078**	0.0463
(-100, 0)	(0, 90)	**-0.0120**	0.0264	**0.0659**	1.10e-94	**0.0090**	0.0267
(-100, 0)	(0, 95)	**-0.0113**	0.0398	**0.0667**	3.70e-94	**0.0102**	0.0144
(-100, 0)	(0, 100)	**-0.0111**	0.0475	**0.0678**	2.40e-94	**0.0114**	0.0075

Table B.5 **Executives - Statuses** Robustness Analysis Results for Different Time Ranges with Before Event Range as (-100, 0)

Event Range		*Rho*		*Gamma*		*Beta*	
Before	After	Value	P-Value	Value	P-Value	Value	P-Value
(-100, 0)	(0, 5)	**0.0266**	0.0000	**-0.0165**	0.0000	**-0.0037**	0.0059
(-100, 0)	(0, 10)	**0.0242**	0.0000	**-0.0131**	0.0000	**-0.0039**	0.0070
(-100, 0)	(0, 15)	**0.0215**	0.0000	**-0.0098**	1.00e-05	**-0.0044**	0.0049
(-100, 0)	(0, 20)	**0.0192**	0.0000	**-0.0070**	0.0011	**-0.0051**	0.0024
(-100, 0)	(0, 25)	**0.0174**	0.0000	**-0.0047**	0.0253	**-0.0057**	0.0014
(-100, 0)	(0, 30)	**0.0174**	0.0000	-0.0020	0.3323	**-0.0063**	0.0008
(-100, 0)	(0, 35)	**0.0188**	0.0000	0.0008	0.6884	**-0.0068**	0.0005
(-100, 0)	(0, 40)	**0.0200**	0.0000	**0.0040**	0.0451	**-0.0072**	0.0004
(-100, 0)	(0, 45)	**0.0207**	0.0000	**0.0075**	0.0002	**-0.0077**	0.0003
(-100, 0)	(0, 50)	**0.0222**	0.0000	**0.0110**	0.0000	**-0.0083**	0.0002
(-100, 0)	(0, 55)	**0.0233**	4.60e-11	**0.0145**	4.40e-12	**-0.0087**	0.0002
(-100, 0)	(0, 60)	**0.0249**	5.10e-12	**0.0178**	6.20e-17	**-0.0091**	0.0002
(-100, 0)	(0, 65)	**0.0259**	1.60e-12	**0.0210**	2.80e-22	**-0.0093**	0.0002
(-100, 0)	(0, 70)	**0.0262**	2.40e-12	**0.0238**	3.20e-27	**-0.0094**	0.0003
(-100, 0)	(0, 75)	**0.0268**	2.20e-12	**0.0264**	6.40e-32	**-0.0093**	0.0006
(-100, 0)	(0, 80)	**0.0280**	8.80e-13	**0.0286**	2.00e-35	**-0.0092**	0.0012
(-100, 0)	(0, 85)	**0.0298**	1.50e-13	**0.0309**	1.30e-38	**-0.0089**	0.0026
(-100, 0)	(0, 90)	**0.0320**	1.70e-14	**0.0329**	9.60e-41	**-0.0085**	0.0061
(-100, 0)	(0, 95)	**0.0342**	2.60e-15	**0.0347**	4.00e-42	**-0.0081**	0.0126
(-100, 0)	(0, 100)	**0.0363**	4.20e-16	**0.0361**	6.40e-43	**-0.0077**	0.0239

Table B.6 **Executives - Daily Engagement** Robustness Analysis Results for Different Time Ranges with Before Event Range as (-100, 0)

Event Range		*Rho*		*Gamma*		*Beta*	
Before	After	Value	P-Value	Value	P-Value	Value	P-Value
(-100, 0)	(0, 5)	0.0124	0.1430	**0.0328**	4.30e-11	**0.0128**	0.0000
(-100, 0)	(0, 10)	**0.0165**	0.0083	**0.0366**	3.10e-23	**0.0133**	0.0000
(-100, 0)	(0, 15)	**0.0158**	0.0032	**0.0383**	8.60e-34	**0.0137**	0.0000
(-100, 0)	(0, 20)	**0.0138**	0.0050	**0.0436**	5.30e-51	**0.0143**	0.0000
(-100, 0)	(0, 25)	**0.0102**	0.0266	**0.0452**	3.30e-62	**0.0148**	0.0000
(-100, 0)	(0, 30)	**0.0089**	0.0452	**0.0480**	8.50e-76	**0.0151**	0.0000
(-100, 0)	(0, 35)	0.0065	0.1305	**0.0497**	2.20e-86	**0.0149**	0.0000
(-100, 0)	(0, 40)	0.0051	0.2207	**0.0510**	1.80e-95	**0.0145**	0.0000
(-100, 0)	(0, 45)	0.0038	0.3603	**0.0530**	7.60e-106	**0.0137**	0.0000
(-100, 0)	(0, 50)	0.0028	0.4879	**0.0547**	7.60e-115	**0.0130**	0.0000
(-100, 0)	(0, 55)	0.0028	0.4957	**0.0567**	2.30e-124	**0.0128**	0.0000
(-100, 0)	(0, 60)	0.0043	0.2879	**0.0579**	3.10e-130	**0.0130**	0.0000
(-100, 0)	(0, 65)	0.0059	0.1472	**0.0586**	2.60e-133	**0.0133**	0.0000
(-100, 0)	(0, 70)	0.0070	0.0836	**0.0596**	1.60e-137	**0.0138**	0.0000
(-100, 0)	(0, 75)	0.0075	0.0624	**0.0599**	2.60e-139	**0.0143**	0.0000
(-100, 0)	(0, 80)	0.0069	0.0874	**0.0609**	2.00e-143	**0.0149**	0.0000
(-100, 0)	(0, 85)	0.0051	0.2060	**0.0612**	4.50e-145	**0.0155**	0.0000
(-100, 0)	(0, 90)	0.0042	0.3021	**0.0609**	2.20e-144	**0.0159**	0.0000
(-100, 0)	(0, 95)	0.0033	0.4184	**0.0607**	2.00e-143	**0.0163**	0.0000
(-100, 0)	(0, 100)	0.0029	0.4772	**0.0601**	2.40e-140	**0.0165**	0.0000

Table B.7 **Companies - Followers** Robustness Analysis Results for 7 Day Difference Time Series Values

Event Range		*Rho*		*Gamma*		*Beta*	
Before	After	Value	P-Value	Value	P-Value	Value	P-Value
(-50, 0)	(0, 5)	**0.0016**	0.0006	-0.0005	0.1671	0.0002	0.1308
(-50, 0)	(0, 10)	**0.0019**	0.0000	**-0.0007**	0.0020	0.0002	0.1530
(-50, 0)	(0, 15)	**0.0015**	0.0000	**-0.0008**	0.0001	0.0002	0.1199
(-50, 0)	(0, 20)	**0.0014**	0.0000	**-0.0008**	1.00e-05	0.0003	0.0558
(-50, 0)	(0, 25)	**0.0012**	0.0000	**-0.0008**	0.0000	**0.0003**	0.0456
(-50, 0)	(0, 30)	**0.0011**	0.0000	**-0.0008**	0.0000	**0.0003**	0.0390
(-50, 0)	(0, 35)	**0.0009**	4.00e-05	**-0.0007**	0.0000	**0.0003**	0.0272
(-50, 0)	(0, 40)	**0.0008**	2.00e-05	**-0.0007**	0.0000	**0.0003**	0.0263
(-50, 0)	(0, 45)	**0.0007**	9.00e-05	**-0.0007**	0.0000	**0.0003**	0.0386
(-50, 0)	(0, 50)	**0.0007**	0.0001	**-0.0008**	0.0000	0.0003	0.0535
(-50, 0)	(0, 55)	**0.0007**	5.00e-05	**-0.0008**	6.30e-12	0.0002	0.0699
(-50, 0)	(0, 60)	**0.0007**	7.00e-05	**-0.0008**	7.70e-13	0.0002	0.0880
(-50, 0)	(0, 65)	**0.0006**	0.0002	**-0.0008**	1.70e-13	0.0002	0.0907
(-50, 0)	(0, 70)	**0.0005**	0.0014	**-0.0008**	1.70e-13	0.0002	0.0964
(-50, 0)	(0, 75)	**0.0004**	0.0065	**-0.0008**	1.60e-13	0.0002	0.1013
(-50, 0)	(0, 80)	**0.0004**	0.0095	**-0.0008**	2.50e-14	0.0002	0.1100
(-50, 0)	(0, 85)	**0.0003**	0.0210	**-0.0008**	3.20e-14	0.0002	0.1414
(-50, 0)	(0, 90)	**0.0003**	0.0331	**-0.0008**	2.30e-15	0.0002	0.1528
(-50, 0)	(0, 95)	**0.0003**	0.0357	**-0.0008**	2.30e-17	0.0002	0.1504
(-50, 0)	(0, 100)	**0.0003**	0.0475	**-0.0008**	8.60e-19	0.0002	0.1614

Table B.8 **Companies - Statuses** Robustness Analysis Results for 7 Day Difference Time Series Values

Event Range		*Rho*		*Gamma*		*Beta*	
Before	After	Value	P-Value	Value	P-Value	Value	P-Value
(-50, 0)	(0, 5)	**0.0023**	6.00e-05	-0.0004	0.3468	-0.0003	0.0823
(-50, 0)	(0, 10)	**0.0020**	0.0000	**-0.0009**	0.0025	-0.0003	0.0583
(-50, 0)	(0, 15)	**0.0016**	1.00e-05	**-0.0010**	2.00e-05	**-0.0004**	0.0432
(-50, 0)	(0, 20)	**0.0016**	0.0000	**-0.0011**	0.0000	-0.0003	0.0717
(-50, 0)	(0, 25)	**0.0012**	2.00e-05	**-0.0009**	0.0000	-0.0003	0.0578
(-50, 0)	(0, 30)	**0.0011**	1.00e-05	**-0.0009**	0.0000	**-0.0003**	0.0473
(-50, 0)	(0, 35)	**0.0010**	5.00e-05	**-0.0009**	0.0000	-0.0003	0.0510
(-50, 0)	(0, 40)	**0.0010**	3.00e-05	**-0.0010**	0.0000	**-0.0003**	0.0496
(-50, 0)	(0, 45)	**0.0010**	1.00e-05	**-0.0010**	2.30e-12	**-0.0003**	0.0386
(-50, 0)	(0, 50)	**0.0010**	0.0000	**-0.0011**	1.60e-15	**-0.0004**	0.0232
(-50, 0)	(0, 55)	**0.0011**	0.0000	**-0.0012**	4.10e-19	**-0.0004**	0.0179
(-50, 0)	(0, 60)	**0.0011**	0.0000	**-0.0013**	8.00e-22	**-0.0004**	0.0157
(-50, 0)	(0, 65)	**0.0010**	0.0000	**-0.0013**	7.60e-23	**-0.0004**	0.0148
(-50, 0)	(0, 70)	**0.0010**	0.0000	**-0.0013**	5.60e-25	**-0.0004**	0.0146
(-50, 0)	(0, 75)	**0.0009**	0.0000	**-0.0013**	1.40e-24	**-0.0004**	0.0117
(-50, 0)	(0, 80)	**0.0008**	0.0000	**-0.0013**	5.40e-25	**-0.0004**	0.0098
(-50, 0)	(0, 85)	**0.0008**	0.0000	**-0.0013**	4.70e-27	**-0.0004**	0.0066
(-50, 0)	(0, 90)	**0.0008**	0.0000	**-0.0013**	4.40e-29	**-0.0004**	0.0054
(-50, 0)	(0, 95)	**0.0008**	0.0000	**-0.0013**	4.60e-32	**-0.0004**	0.0049
(-50, 0)	(0, 100)	**0.0009**	0.0000	**-0.0014**	9.20e-36	**-0.0004**	0.0035

Table B.9 **Companies - Daily Engagement** Robustness Analysis Results for 7 Day Difference Time Series Values

Event Range		*Rho*		*Gamma*		*Beta*	
Before	After	Value	P-Value	Value	P-Value	Value	P-Value
(-50, 0)	(0, 5)	**0.0700**	6.90e-37	0.0018	0.6271	0.0005	0.7867
(-50, 0)	(0, 10)	**0.0247**	0.0000	0.0020	0.4705	-0.0001	0.9513
(-50, 0)	(0, 15)	**0.0107**	0.0024	0.0014	0.5526	-0.0003	0.8579
(-50, 0)	(0, 20)	0.0050	0.1146	0.0015	0.4931	-0.0006	0.7541
(-50, 0)	(0, 25)	0.0036	0.2296	0.0020	0.3187	-0.0006	0.7398
(-50, 0)	(0, 30)	0.0011	0.6948	0.0025	0.1847	-0.0004	0.8178
(-50, 0)	(0, 35)	0.0009	0.7302	0.0024	0.1814	-0.0004	0.8093
(-50, 0)	(0, 40)	0.0007	0.7712	0.0019	0.2820	-0.0003	0.8829
(-50, 0)	(0, 45)	-0.0006	0.8179	0.0027	0.1070	-0.0002	0.8913
(-50, 0)	(0, 50)	-0.0002	0.9284	0.0028	0.0936	0.0002	0.9217
(-50, 0)	(0, 55)	0.0015	0.5301	0.0016	0.3151	0.0002	0.9234
(-50, 0)	(0, 60)	0.0001	0.9516	0.0014	0.3969	8.72e-05	0.9619
(-50, 0)	(0, 65)	-0.0003	0.9123	0.0018	0.2622	2.55e-05	0.9888
(-50, 0)	(0, 70)	-0.0007	0.7611	0.0025	0.1040	-0.0002	0.9139
(-50, 0)	(0, 75)	-0.0008	0.7217	0.0023	0.1336	-0.0002	0.9270
(-50, 0)	(0, 80)	-0.0001	0.9615	0.0019	0.2141	-0.0002	0.9040
(-50, 0)	(0, 85)	-0.0005	0.8209	0.0020	0.1777	-0.0002	0.8992
(-50, 0)	(0, 90)	0.0004	0.8709	0.0012	0.4167	-4.48e-05	0.9801
(-50, 0)	(0, 95)	0.0002	0.9400	0.0014	0.3326	-7.69e-05	0.9658
(-50, 0)	(0, 100)	-0.0001	0.9594	0.0011	0.4543	5.35e-06	0.9976

Table B.10 **Executives - Followers** Robustness Analysis Results for 7 Day Difference Time Series Values

Event Range		*Rho*		*Gamma*		*Beta*	
Before	After	Value	P-Value	Value	P-Value	Value	P-Value
(-50, 0)	(0, 5)	**0.0025**	0.0000	-0.0003	0.2854	**0.0009**	0.0000
(-50, 0)	(0, 10)	**0.0014**	1.00e-05	-0.0004	0.0665	**0.0009**	0.0000
(-50, 0)	(0, 15)	**0.0007**	0.0118	**-0.0003**	0.0403	**0.0009**	0.0000
(-50, 0)	(0, 20)	0.0004	0.1339	**-0.0004**	0.0095	**0.0009**	0.0000
(-50, 0)	(0, 25)	0.0002	0.2726	**-0.0004**	0.0020	**0.0009**	0.0000
(-50, 0)	(0, 30)	0.0002	0.2530	**-0.0004**	0.0026	**0.0009**	0.0000
(-50, 0)	(0, 35)	0.0003	0.1341	**-0.0004**	0.0015	**0.0008**	0.0000
(-50, 0)	(0, 40)	0.0002	0.1788	**-0.0003**	0.0068	**0.0009**	3.20e-11
(-50, 0)	(0, 45)	0.0002	0.3827	**-0.0003**	0.0120	**0.0009**	8.20e-12
(-50, 0)	(0, 50)	0.0001	0.5310	**-0.0003**	0.0088	**0.0009**	1.10e-11
(-50, 0)	(0, 55)	1.72e-05	0.9156	**-0.0002**	0.0279	**0.0009**	3.90e-12
(-50, 0)	(0, 60)	2.33e-05	0.8820	**-0.0002**	0.0095	**0.0009**	8.60e-13
(-50, 0)	(0, 65)	1.09e-05	0.9432	**-0.0003**	0.0026	**0.0009**	5.70e-13
(-50, 0)	(0, 70)	5.95e-06	0.9681	**-0.0003**	0.0006	**0.0009**	4.90e-13
(-50, 0)	(0, 75)	2.99e-05	0.8359	**-0.0004**	3.00e-05	**0.0009**	1.60e-13
(-50, 0)	(0, 80)	4.42e-05	0.7539	**-0.0004**	0.0000	**0.0009**	8.30e-14
(-50, 0)	(0, 85)	-2.00e-05	0.8852	**-0.0004**	0.0000	**0.0009**	2.60e-14
(-50, 0)	(0, 90)	-7.20e-05	0.5964	**-0.0004**	0.0000	**0.0009**	4.00e-15
(-50, 0)	(0, 95)	-8.94e-05	0.5025	**-0.0004**	0.0000	**0.0009**	1.10e-15
(-50, 0)	(0, 100)	-0.0001	0.3092	**-0.0004**	0.0000	**0.0009**	3.40e-16

Table B.11 **Executives - Statuses** Robustness Analysis Results for 7 Day Difference Time Series Values

Event Range		*Rho*		*Gamma*		*Beta*	
Before	After	Value	P-Value	Value	P-Value	Value	P-Value
(-50, 0)	(0, 5)	**0.0015**	0.0008	-9.27e-05	0.7165	**0.0004**	0.0114
(-50, 0)	(0, 10)	0.0006	0.0525	0.0002	0.3136	**0.0004**	0.0096
(-50, 0)	(0, 15)	0.0002	0.3858	-6.64e-05	0.6845	**0.0003**	0.0285
(-50, 0)	(0, 20)	5.11e-05	0.8366	-0.0002	0.3014	**0.0003**	0.0292
(-50, 0)	(0, 25)	-0.0002	0.3817	-0.0001	0.4337	**0.0003**	0.0227
(-50, 0)	(0, 30)	-0.0004	0.0703	4.09e-05	0.7481	**0.0003**	0.0194
(-50, 0)	(0, 35)	-0.0003	0.1331	-7.21e-06	0.9519	**0.0003**	0.0149
(-50, 0)	(0, 40)	-0.0003	0.1403	2.21e-06	0.9845	**0.0004**	0.0053
(-50, 0)	(0, 45)	-0.0003	0.1631	1.38e-05	0.8994	**0.0004**	0.0037
(-50, 0)	(0, 50)	-0.0003	0.1389	5.24e-06	0.9601	**0.0004**	0.0057
(-50, 0)	(0, 55)	-0.0002	0.1453	-8.37e-06	0.9338	**0.0004**	0.0055
(-50, 0)	(0, 60)	-0.0002	0.3442	-5.69e-05	0.5608	**0.0004**	0.0033
(-50, 0)	(0, 65)	-0.0001	0.5012	-0.0001	0.1910	**0.0004**	0.0025
(-50, 0)	(0, 70)	-0.0001	0.4246	-0.0002	0.0707	**0.0004**	0.0015
(-50, 0)	(0, 75)	-8.63e-05	0.5694	**-0.0002**	0.0132	**0.0004**	0.0014
(-50, 0)	(0, 80)	-5.73e-05	0.6990	**-0.0003**	0.0016	**0.0004**	0.0015
(-50, 0)	(0, 85)	-8.81e-05	0.5441	**-0.0003**	0.0013	**0.0004**	0.0009
(-50, 0)	(0, 90)	-0.0001	0.3159	**-0.0003**	0.0016	**0.0004**	0.0004
(-50, 0)	(0, 95)	-0.0001	0.2900	**-0.0003**	0.0004	**0.0004**	0.0003
(-50, 0)	(0, 100)	-0.0002	0.2312	**-0.0003**	0.0001	**0.0004**	0.0002

Table B.12 **Executives - Daily Engagement** Robustness Analysis Results for 7 Day Difference Time Series Values

Event Range		*Rho*		*Gamma*		*Beta*	
Before	After	Value	P-Value	Value	P-Value	Value	P-Value
(-50, 0)	(0, 5)	**0.0082**	0.0407	0.0002	0.9491	0.0006	0.6518
(-50, 0)	(0, 10)	**0.0088**	0.0032	0.0017	0.3412	0.0005	0.7273
(-50, 0)	(0, 15)	**0.0064**	0.0115	0.0002	0.8681	0.0007	0.5986
(-50, 0)	(0, 20)	**0.0049**	0.0325	0.0005	0.7020	0.0006	0.6449
(-50, 0)	(0, 25)	0.0026	0.2164	0.0002	0.8918	0.0006	0.6438
(-50, 0)	(0, 30)	0.0012	0.5393	0.0008	0.5215	0.0005	0.7130
(-50, 0)	(0, 35)	0.0008	0.6753	0.0008	0.4820	0.0002	0.8953
(-50, 0)	(0, 40)	0.0013	0.4743	-3.57e-07	0.9997	9.78e-05	0.9411
(-50, 0)	(0, 45)	0.0015	0.4127	2.57e-05	0.9804	-0.0002	0.8733
(-50, 0)	(0, 50)	0.0014	0.4175	0.0005	0.6231	-0.0002	0.8963
(-50, 0)	(0, 55)	0.0007	0.6619	0.0005	0.6293	5.37e-06	0.9967
(-50, 0)	(0, 60)	0.0009	0.5841	0.0005	0.6135	0.0002	0.9055
(-50, 0)	(0, 65)	0.0011	0.4907	0.0002	0.8078	0.0003	0.8265
(-50, 0)	(0, 70)	0.0013	0.4315	0.0002	0.8553	0.0004	0.7747
(-50, 0)	(0, 75)	0.0012	0.4450	0.0002	0.8712	0.0003	0.8210
(-50, 0)	(0, 80)	6.52e-05	0.9666	0.0003	0.7257	0.0005	0.7069
(-50, 0)	(0, 85)	-0.0005	0.7236	0.0004	0.6531	0.0004	0.7372
(-50, 0)	(0, 90)	-0.0004	0.8170	0.0002	0.8161	0.0005	0.6966
(-50, 0)	(0, 95)	-0.0002	0.9058	0.0001	0.8792	0.0003	0.7869
(-50, 0)	(0, 100)	0.0001	0.9428	-8.68e-05	0.9211	4.14e-05	0.9742

Table B.13 **Companies - Followers** Robustness Analysis Results for Last 7 Day Mean Difference Time Series Values

Event Range		*Rho*		*Gamma*		*Beta*	
Before	After	Value	P-Value	Value	P-Value	Value	P-Value
(-50, 0)	(0, 5)	**0.0014**	0.0000	-0.0003	0.2141	0.0001	0.2913
(-50, 0)	(0, 10)	**0.0012**	0.0000	**-0.0004**	0.0027	9.32e-05	0.3290
(-50, 0)	(0, 15)	**0.0009**	0.0000	**-0.0004**	0.0003	0.0001	0.2513
(-50, 0)	(0, 20)	**0.0009**	0.0000	**-0.0004**	5.00e-05	0.0001	0.1423
(-50, 0)	(0, 25)	**0.0007**	0.0000	**-0.0004**	1.00e-05	0.0001	0.1365
(-50, 0)	(0, 30)	**0.0006**	0.0000	**-0.0004**	0.0000	0.0001	0.1173
(-50, 0)	(0, 35)	**0.0005**	7.00e-05	**-0.0004**	2.00e-05	0.0001	0.0904
(-50, 0)	(0, 40)	**0.0005**	2.00e-05	**-0.0004**	0.0000	0.0001	0.0993
(-50, 0)	(0, 45)	**0.0005**	0.0001	**-0.0004**	0.0000	0.0001	0.1278
(-50, 0)	(0, 50)	**0.0004**	9.00e-05	**-0.0004**	0.0000	0.0001	0.1689
(-50, 0)	(0, 55)	**0.0004**	4.00e-05	**-0.0005**	0.0000	0.0001	0.2076
(-50, 0)	(0, 60)	**0.0004**	7.00e-05	**-0.0005**	6.00e-11	9.43e-05	0.2458
(-50, 0)	(0, 65)	**0.0004**	0.0002	**-0.0005**	1.60e-11	9.31e-05	0.2455
(-50, 0)	(0, 70)	**0.0003**	0.0018	**-0.0004**	3.50e-11	8.93e-05	0.2596
(-50, 0)	(0, 75)	**0.0003**	0.0043	**-0.0004**	1.50e-11	8.56e-05	0.2748
(-50, 0)	(0, 80)	**0.0003**	0.0075	**-0.0004**	4.90e-12	8.08e-05	0.2990
(-50, 0)	(0, 85)	**0.0002**	0.0150	**-0.0004**	4.70e-12	7.17e-05	0.3535
(-50, 0)	(0, 90)	**0.0002**	0.0210	**-0.0005**	3.00e-13	6.83e-05	0.3703
(-50, 0)	(0, 95)	**0.0002**	0.0221	**-0.0005**	8.40e-15	6.79e-05	0.3667
(-50, 0)	(0, 100)	**0.0002**	0.0312	**-0.0005**	4.20e-16	6.32e-05	0.3952

Table B.14 **Companies - Statuses** Robustness Analysis Results for Last 7 Day Mean Difference Time Series Values

Event Range		*Rho*		*Gamma*		*Beta*	
Before	After	Value	P-Value	Value	P-Value	Value	P-Value
(-50, 0)	(0, 5)	**0.0018**	0.0000	-0.0004	0.0930	-0.0002	0.0811
(-50, 0)	(0, 10)	**0.0012**	0.0000	**-0.0006**	0.0004	-0.0002	0.0592
(-50, 0)	(0, 15)	**0.0010**	1.00e-05	**-0.0007**	0.0000	**-0.0002**	0.0487
(-50, 0)	(0, 20)	**0.0010**	0.0000	**-0.0007**	0.0000	-0.0002	0.0834
(-50, 0)	(0, 25)	**0.0007**	6.00e-05	**-0.0006**	0.0000	-0.0002	0.0603
(-50, 0)	(0, 30)	**0.0007**	2.00e-05	**-0.0006**	0.0000	-0.0002	0.0547
(-50, 0)	(0, 35)	**0.0006**	0.0001	**-0.0005**	0.0000	-0.0002	0.0582
(-50, 0)	(0, 40)	**0.0006**	6.00e-05	**-0.0006**	0.0000	-0.0002	0.0537
(-50, 0)	(0, 45)	**0.0006**	2.00e-05	**-0.0006**	1.20e-11	**-0.0002**	0.0428
(-50, 0)	(0, 50)	**0.0006**	0.0000	**-0.0007**	1.20e-14	**-0.0002**	0.0261
(-50, 0)	(0, 55)	**0.0007**	0.0000	**-0.0007**	2.00e-17	**-0.0002**	0.0221
(-50, 0)	(0, 60)	**0.0006**	0.0000	**-0.0008**	8.40e-20	**-0.0002**	0.0191
(-50, 0)	(0, 65)	**0.0006**	0.0000	**-0.0007**	3.40e-20	**-0.0002**	0.0188
(-50, 0)	(0, 70)	**0.0006**	0.0000	**-0.0008**	6.00e-22	**-0.0002**	0.0195
(-50, 0)	(0, 75)	**0.0005**	1.00e-05	**-0.0007**	3.00e-21	**-0.0002**	0.0154
(-50, 0)	(0, 80)	**0.0005**	1.00e-05	**-0.0007**	5.60e-22	**-0.0002**	0.0128
(-50, 0)	(0, 85)	**0.0005**	1.00e-05	**-0.0008**	7.00e-24	**-0.0002**	0.0091
(-50, 0)	(0, 90)	**0.0005**	1.00e-05	**-0.0008**	1.70e-25	**-0.0002**	0.0080
(-50, 0)	(0, 95)	**0.0005**	0.0000	**-0.0008**	3.50e-28	**-0.0002**	0.0070
(-50, 0)	(0, 100)	**0.0005**	0.0000	**-0.0008**	1.80e-31	**-0.0002**	0.0054

Table B.15 **Companies - Daily Engagement** Robustness Analysis Results for Last 7 Day Mean Difference Time Series Values

Event Range		*Rho*		*Gamma*		*Beta*	
Before	After	Value	P-Value	Value	P-Value	Value	P-Value
(-50, 0)	(0, 5)	**0.0462**	2.70e-28	0.0044	0.1235	0.0002	0.8907
(-50, 0)	(0, 10)	**0.0135**	2.00e-05	0.0024	0.2538	-0.0001	0.9247
(-50, 0)	(0, 15)	**0.0056**	0.0363	0.0011	0.5251	-0.0002	0.8700
(-50, 0)	(0, 20)	0.0030	0.2113	0.0013	0.4213	-0.0004	0.7899
(-50, 0)	(0, 25)	0.0019	0.3804	0.0021	0.1689	-0.0004	0.7745
(-50, 0)	(0, 30)	0.0005	0.8189	0.0019	0.1744	-0.0003	0.8313
(-50, 0)	(0, 35)	0.0007	0.7201	0.0015	0.2793	-0.0002	0.8649
(-50, 0)	(0, 40)	0.0003	0.8569	0.0016	0.2353	-0.0002	0.8826
(-50, 0)	(0, 45)	-0.0003	0.8724	0.0022	0.0808	-0.0002	0.8946
(-50, 0)	(0, 50)	0.0004	0.8450	0.0016	0.1938	0.0001	0.9266
(-50, 0)	(0, 55)	0.0008	0.6718	0.0012	0.3338	6.15e-05	0.9641
(-50, 0)	(0, 60)	0.0003	0.8724	0.0011	0.3456	-2.49e-05	0.9855
(-50, 0)	(0, 65)	-0.0002	0.8954	0.0015	0.1914	-7.12e-05	0.9583
(-50, 0)	(0, 70)	-0.0003	0.8575	0.0016	0.1668	-0.0001	0.9198
(-50, 0)	(0, 75)	-0.0004	0.8334	0.0015	0.1786	-0.0002	0.9050
(-50, 0)	(0, 80)	0.0001	0.9494	0.0014	0.2196	-0.0002	0.8893
(-50, 0)	(0, 85)	-0.0002	0.8867	0.0013	0.2353	-0.0001	0.9146
(-50, 0)	(0, 90)	0.0004	0.8278	0.0009	0.4271	-0.0001	0.9382
(-50, 0)	(0, 95)	0.0002	0.9040	0.0011	0.3025	-0.0001	0.9326
(-50, 0)	(0, 100)	-5.32e-06	0.9973	0.0009	0.4292	-2.36e-05	0.9860

Table B.16 **Executives - Followers** Robustness Analysis Results for 7 Day Mean Difference Time Series Values

Event Range		*Rho*		*Gamma*		*Beta*	
Before	After	Value	P-Value	Value	P-Value	Value	P-Value
(-50, 0)	(0, 5)	**0.0011**	0.0002	-0.0001	0.5322	**0.0006**	0.0000
(-50, 0)	(0, 10)	**0.0005**	0.0118	-0.0002	0.1095	**0.0006**	0.0000
(-50, 0)	(0, 15)	0.0002	0.3386	-0.0002	0.0896	**0.0006**	0.0000
(-50, 0)	(0, 20)	3.36e-05	0.8234	**-0.0002**	0.0253	**0.0006**	0.0000
(-50, 0)	(0, 25)	-1.58e-05	0.9079	**-0.0002**	0.0116	**0.0006**	0.0000
(-50, 0)	(0, 30)	2.33e-05	0.8558	**-0.0002**	0.0118	**0.0005**	0.0000
(-50, 0)	(0, 35)	5.18e-05	0.6673	**-0.0002**	0.0093	**0.0005**	0.0000
(-50, 0)	(0, 40)	2.16e-05	0.8503	**-0.0001**	0.0445	**0.0006**	2.30e-11
(-50, 0)	(0, 45)	-1.71e-05	0.8762	**-0.0001**	0.0373	**0.0006**	1.10e-11
(-50, 0)	(0, 50)	-5.12e-05	0.6283	-0.0001	0.0511	**0.0005**	1.30e-11
(-50, 0)	(0, 55)	-8.32e-05	0.4183	-0.0001	0.0902	**0.0006**	3.60e-12
(-50, 0)	(0, 60)	-8.11e-05	0.4146	**-0.0001**	0.0362	**0.0006**	8.30e-13
(-50, 0)	(0, 65)	-8.06e-05	0.4050	**-0.0001**	0.0129	**0.0006**	7.80e-13
(-50, 0)	(0, 70)	-8.11e-05	0.3883	**-0.0002**	0.0034	**0.0006**	4.90e-13
(-50, 0)	(0, 75)	-6.50e-05	0.4773	**-0.0002**	0.0004	**0.0006**	1.40e-13
(-50, 0)	(0, 80)	-5.51e-05	0.5380	**-0.0002**	5.00e-05	**0.0006**	9.10e-14
(-50, 0)	(0, 85)	-0.0001	0.2310	**-0.0002**	0.0001	**0.0006**	2.50e-14
(-50, 0)	(0, 90)	-0.0001	0.1725	**-0.0002**	0.0001	**0.0006**	3.80e-15
(-50, 0)	(0, 95)	-0.0001	0.1063	**-0.0002**	4.00e-05	**0.0006**	1.30e-15
(-50, 0)	(0, 100)	-0.0002	0.0600	**-0.0002**	2.00e-05	**0.0006**	3.70e-16

Table B.17 **Executives - Statuses** Robustness Analysis Results for 7 Day Mean Difference Time Series Values

Event Range		*Rho*		*Gamma*		*Beta*	
Before	After	Value	P-Value	Value	P-Value	Value	P-Value
(-50, 0)	(0, 5)	**0.0008**	0.0041	-1.12e-05	0.9453	**0.0002**	0.0130
(-50, 0)	(0, 10)	0.0001	0.5001	0.0002	0.1673	**0.0002**	0.0125
(-50, 0)	(0, 15)	6.55e-05	0.7166	-8.22e-05	0.4394	**0.0002**	0.0413
(-50, 0)	(0, 20)	-4.52e-05	0.7767	-8.11e-05	0.3871	**0.0002**	0.0319
(-50, 0)	(0, 25)	-0.0002	0.1366	-3.27e-05	0.7076	**0.0002**	0.0272
(-50, 0)	(0, 30)	**-0.0003**	0.0477	3.13e-05	0.7017	**0.0002**	0.0219
(-50, 0)	(0, 35)	-0.0002	0.0938	-3.54e-06	0.9632	**0.0002**	0.0166
(-50, 0)	(0, 40)	-0.0002	0.0862	1.61e-05	0.8250	**0.0002**	0.0057
(-50, 0)	(0, 45)	-0.0002	0.1158	1.26e-05	0.8572	**0.0002**	0.0056
(-50, 0)	(0, 50)	-0.0002	0.0864	9.20e-06	0.8908	**0.0002**	0.0080
(-50, 0)	(0, 55)	-0.0002	0.1148	3.48e-07	0.9957	**0.0002**	0.0063
(-50, 0)	(0, 60)	-0.0001	0.2792	-3.55e-05	0.5716	**0.0002**	0.0044
(-50, 0)	(0, 65)	-9.94e-05	0.3350	-6.91e-05	0.2552	**0.0002**	0.0032
(-50, 0)	(0, 70)	-0.0001	0.2942	-9.66e-05	0.1002	**0.0003**	0.0020
(-50, 0)	(0, 75)	-7.74e-05	0.4255	**-0.0001**	0.0275	**0.0002**	0.0020
(-50, 0)	(0, 80)	-6.25e-05	0.5099	**-0.0002**	0.0050	**0.0002**	0.0020
(-50, 0)	(0, 85)	-9.08e-05	0.3297	**-0.0002**	0.0060	**0.0003**	0.0012
(-50, 0)	(0, 90)	-0.0001	0.2165	**-0.0001**	0.0057	**0.0003**	0.0006
(-50, 0)	(0, 95)	-0.0001	0.1914	**-0.0002**	0.0019	**0.0003**	0.0005
(-50, 0)	(0, 100)	-0.0001	0.1453	**-0.0002**	0.0006	**0.0003**	0.0004

Table B.18 **Executives - Daily Engagement** Robustness Analysis Results for 7 Day Mean Difference Time Series Values

Event Range		*Rho*		*Gamma*		*Beta*	
Before	After	Value	P-Value	Value	P-Value	Value	P-Value
(-50, 0)	(0, 5)	**0.0067**	0.0225	0.0023	0.1758	0.0005	0.6536
(-50, 0)	(0, 10)	**0.0066**	0.0024	0.0013	0.3001	0.0004	0.6695
(-50, 0)	(0, 15)	0.0033	0.0747	0.0003	0.7559	0.0005	0.6021
(-50, 0)	(0, 20)	0.0031	0.0586	0.0006	0.5565	0.0005	0.6349
(-50, 0)	(0, 25)	0.0014	0.3539	0.0004	0.6642	0.0005	0.6368
(-50, 0)	(0, 30)	0.0007	0.6326	0.0010	0.2454	0.0003	0.7351
(-50, 0)	(0, 35)	0.0004	0.7656	0.0004	0.5852	0.0003	0.7939
(-50, 0)	(0, 40)	0.0010	0.4744	0.0002	0.7958	8.29e-05	0.9316
(-50, 0)	(0, 45)	0.0010	0.4600	0.0004	0.6263	-3.62e-05	0.9701
(-50, 0)	(0, 50)	0.0007	0.5716	0.0004	0.5673	2.56e-05	0.9788
(-50, 0)	(0, 55)	0.0004	0.7671	0.0005	0.4806	0.0001	0.8783
(-50, 0)	(0, 60)	0.0006	0.6260	0.0005	0.4596	0.0002	0.8649
(-50, 0)	(0, 65)	0.0007	0.5594	0.0003	0.6552	0.0003	0.7334
(-50, 0)	(0, 70)	0.0007	0.5583	0.0003	0.7060	0.0003	0.7771
(-50, 0)	(0, 75)	0.0006	0.5796	0.0003	0.6330	0.0003	0.7389
(-50, 0)	(0, 80)	-8.93e-05	0.9371	0.0004	0.5364	0.0003	0.7117
(-50, 0)	(0, 85)	-0.0004	0.7288	0.0004	0.5283	0.0004	0.6948
(-50, 0)	(0, 90)	-0.0002	0.8866	0.0003	0.6603	0.0004	0.6943
(-50, 0)	(0, 95)	-9.00e-05	0.9345	0.0003	0.6546	0.0002	0.7947
(-50, 0)	(0, 100)	4.45e-05	0.9672	0.0001	0.8672	0.0001	0.9131

Table B.19 **Companies - Followers** Robustness Analysis Results for Multiple After Event Coefficients

Event Range		*Rho1*		*Rho2*		*Rho3*		*Gamma1*		*Gamma2*		*Gamma3*		*Beta*	
Before	After	Value	P-Value	Value	P-Value	Value	P-Value	Value	P-Value	Value	P-Value	Value	P-Value	Value	P-Value
(-90, 0)	(0, 30)	**0.0482**	1.00e-14	**0.0537**	6.80e-18	**0.0411**	4.10e-11	**-0.0151**	0.0003	-0.0026	0.5407	**0.0122**	0.0039	**0.0050**	0.0169
(-90, 0)	(0, 60)	**0.0508**	7.50e-15	**0.0444**	1.10e-11	**0.0394**	0.0000	**-0.0088**	0.0456	**0.0120**	0.0067	**0.0194**	1.00e-05	**0.0074**	0.0118
(-90, 0)	(0, 90)	**0.0486**	0.0000	**0.0432**	0.0000	-0.0114	0.1542	-0.0021	0.7020	**0.0166**	0.0022	**0.0280**	0.0000	0.0078	0.0606
(-50, 0)	(0, 30)	**0.0473**	5.70e-13	**0.0528**	8.60e-16	**0.0403**	0.0000	**-0.0100**	0.0242	0.0025	0.5758	**0.0172**	0.0001	0.0045	0.1117
(-50, 0)	(0, 60)	**0.0499**	5.60e-11	**0.0435**	0.0000	**0.0385**	0.0000	-0.0038	0.4618	**0.0171**	0.0009	**0.0244**	0.0000	0.0081	0.0548
(-50, 0)	(0, 90)	**0.0486**	0.0000	**0.0432**	1.00e-05	-0.0115	0.2347	0.0028	0.6690	**0.0215**	0.0010	**0.0328**	0.0000	0.0082	0.1776

Table B.20 **Companies - Statuses** Robustness Analysis Results for Multiple After Event Coefficients

Event Range		*Rho*1		*Rho*2		*Rho*3		*Gamma*1		*Gamma*2		*Gamma*3		*Beta*	
Before	After	Value	P-Value	Value	P-Value	Value	P-Value	Value	P-Value	Value	P-Value	Value	P-Value	Value	P-Value
(-90, 0)	(0, 30)	**0.0358**	1.40e-11	**0.0287**	0.0000	**0.0186**	0.0004	**-0.0203**	0.0000	**-0.0169**	0.0000	**-0.0128**	0.0004	**0.0053**	0.0028
(-90, 0)	(0, 60)	**0.0321**	0.0000	**0.0137**	0.0229	**0.0208**	0.0006	**-0.0185**	1.00e-05	-0.0074	0.0695	-0.0066	0.1067	0.0047	0.0818
(-90, 0)	(0, 90)	**0.0278**	4.00e-05	**0.0171**	0.0119	0.0124	0.0687	**-0.0166**	0.0003	-0.0051	0.2649	-0.0086	0.0618	0.0035	0.3229
(-50, 0)	(0, 30)	**0.0352**	0.0000	**0.0282**	0.0000	**0.0181**	0.0019	**-0.0138**	0.0004	**-0.0104**	0.0083	-0.0063	0.1097	0.0018	0.4781
(-50, 0)	(0, 60)	**0.0315**	1.00e-05	0.0131	0.0680	**0.0202**	0.0050	**-0.0120**	0.0136	-0.0009	0.8551	-6.36e-05	0.9896	0.0021	0.5979
(-50, 0)	(0, 90)	**0.0274**	0.0009	**0.0167**	0.0427	0.0120	0.1463	-0.0101	0.0693	0.0014	0.8073	-0.0021	0.7057	0.0011	0.8297

Table B.21 **Companies - Daily Engagement** Robustness Analysis Results for Multiple After Event Coefficients

Event Range		*Rho*1		*Rho*2		*Rho*3		*Gamma*1		*Gamma*2		*Gamma*3		*Beta*	
Before	After	Value	P-Value	Value	P-Value	Value	P-Value	Value	P-Value	Value	P-Value	Value	P-Value	Value	P-Value
(-90, 0)	(0, 30)	**0.1551**	8.30e-74	**0.0657**	1.30e-14	**0.0428**	0.0000	-0.0022	0.7037	-0.0053	0.3609	0.0096	0.0959	**-0.0415**	1.80e-47
(-90, 0)	(0, 60)	**0.1108**	8.60e-53	**0.0395**	0.0000	**0.0342**	0.0000	-0.0037	0.4548	**0.0111**	0.0231	**0.0170**	0.0005	**-0.0463**	3.90e-46
(-90, 0)	(0, 90)	**0.0886**	5.40e-37	**0.0351**	0.0000	0.0066	0.3444	0.0006	0.9044	**0.0153**	0.0012	**0.0409**	4.80e-18	**-0.0523**	4.70e-47
(-50, 0)	(0, 30)	**0.1581**	5.40e-65	**0.0687**	1.30e-13	**0.0458**	0.0000	-0.0058	0.3535	-0.0089	0.1562	0.0060	0.3406	**-0.0500**	3.00e-36
(-50, 0)	(0, 60)	**0.1140**	2.50e-43	**0.0428**	0.0000	**0.0374**	1.00e-05	-0.0072	0.1953	0.0076	0.1759	**0.0134**	0.0164	**-0.0551**	1.80e-33
(-50, 0)	(0, 90)	**0.0921**	1.50e-29	**0.0386**	0.0000	0.0101	0.2165	-0.0032	0.5649	**0.0116**	0.0364	**0.0371**	1.80e-11	**-0.0618**	1.80e-33

Table B.22 **Executives - Followers** Robustness Analysis Results for Multiple After Event Coefficients

Event Range		*Rho*1		*Rho*2		*Rho*3		*Gamma*1		*Gamma*2		*Gamma*3		*Beta*	
Before	After	Value	P-Value	Value	P-Value	Value	P-Value	Value	P-Value	Value	P-Value	Value	P-Value	Value	P-Value
(-90, 0)	(0, 30)	**0.0165**	0.0272	0.0004	0.9546	-0.0133	0.0762	**0.0112**	0.0111	**0.0352**	1.50e-15	**0.0454**	7.00e-25	-0.0017	0.5194
(-90, 0)	(0, 60)	0.0086	0.2616	-0.0148	0.0534	**-0.0299**	0.0001	**0.0226**	0.0000	**0.0532**	5.40e-32	**0.0869**	2.20e-82	0.0038	0.2871
(-90, 0)	(0, 90)	0.0010	0.9045	**-0.0258**	0.0014	-0.0129	0.1107	**0.0303**	0.0000	**0.0787**	3.00e-61	**0.0886**	4.00e-77	**0.0103**	0.0177
(-50, 0)	(0, 30)	0.0150	0.0871	-0.0012	0.8951	-0.0149	0.0892	**0.0110**	0.0327	**0.0350**	1.10e-11	**0.0452**	1.60e-18	0.0036	0.3557
(-50, 0)	(0, 60)	0.0071	0.4396	-0.0163	0.0779	**-0.0314**	0.0007	**0.0220**	5.00e-05	**0.0526**	4.40e-22	**0.0863**	1.40e-56	0.0100	0.0574
(-50, 0)	(0, 90)	-0.0008	0.9343	**-0.0276**	0.0050	-0.0147	0.1352	**0.0298**	0.0000	**0.0782**	1.30e-41	**0.0881**	2.60e-52	**0.0176**	0.0055

Table B.23 **Executives - Statuses** Robustness Analysis Results for Multiple After Event Coefficients

Event Range		*Rho*1		*Rho*2		*Rho*3		*Gamma*1		*Gamma*2		*Gamma*3		*Beta*	
Before	After	Value	P-Value	Value	P-Value	Value	P-Value	Value	P-Value	Value	P-Value	Value	P-Value	Value	P-Value
(-90, 0)	(0, 30)	**0.0224**	0.0001	**0.0124**	0.0318	**0.0120**	0.0372	**-0.0131**	0.0001	-0.0009	0.7942	**0.0080**	0.0187	**-0.0053**	0.0095
(-90, 0)	(0, 60)	**0.0172**	0.0022	**0.0187**	0.0009	**0.0329**	0.0000	**-0.0074**	0.0250	**0.0146**	1.00e-05	**0.0448**	2.00e-41	**-0.0078**	0.0028
(-90, 0)	(0, 90)	**0.0151**	0.0158	**0.0301**	0.0000	**0.0439**	2.10e-12	-0.0025	0.4898	**0.0370**	9.10e-24	**0.0625**	1.10e-64	**-0.0067**	0.0474
(-50, 0)	(0, 30)	**0.0171**	0.0103	0.0070	0.2900	0.0067	0.3158	**-0.0113**	0.0040	0.0009	0.8208	**0.0098**	0.0126	-0.0014	0.6382
(-50, 0)	(0, 60)	0.0117	0.0818	**0.0132**	0.0499	**0.0274**	5.00e-05	-0.0060	0.1281	**0.0161**	5.00e-05	**0.0462**	2.00e-31	-0.0044	0.2524
(-50, 0)	(0, 90)	0.0093	0.2203	**0.0243**	0.0013	**0.0381**	0.0000	-0.0012	0.7878	**0.0383**	8.30e-18	**0.0639**	1.80e-46	-0.0023	0.6403

Table B.24 **Executives - Daily Engagement** Robustness Analysis Results for Multiple After Event Coefficients

Event Range		*Rho*1		*Rho*2		*Rho*3		*Gamma*1		*Gamma*2		*Gamma*3		*Beta*	
Before	After	Value	P-Value	Value	P-Value	Value	P-Value	Value	P-Value	Value	P-Value	Value	P-Value	Value	P-Value
(-90, 0)	(0, 30)	**0.0168**	0.0194	0.0115	0.1109	-0.0008	0.9103	**0.0354**	6.20e-17	**0.0493**	2.50e-31	**0.0556**	2.30e-39	**0.0147**	0.0000
(-90, 0)	(0, 60)	**0.0138**	0.0276	-0.0037	0.5535	0.0026	0.6778	**0.0425**	7.40e-31	**0.0573**	8.70e-55	**0.0707**	2.80e-82	**0.0130**	1.00e-05
(-90, 0)	(0, 90)	0.0092	0.1211	0.0001	0.9825	0.0043	0.4722	**0.0470**	8.60e-41	**0.0668**	9.00e-81	**0.0658**	2.10e-78	**0.0157**	0.0000
(-50, 0)	(0, 30)	**0.0182**	0.0204	0.0129	0.1016	0.0006	0.9403	**0.0315**	1.00e-11	**0.0454**	1.10e-22	**0.0517**	6.10e-29	**0.0130**	0.0002
(-50, 0)	(0, 60)	**0.0149**	0.0382	-0.0026	0.7162	0.0037	0.6066	**0.0386**	6.00e-20	**0.0535**	9.30e-37	**0.0668**	2.10e-56	**0.0109**	0.0076
(-50, 0)	(0, 90)	0.0107	0.1260	0.0016	0.8197	0.0057	0.4112	**0.0431**	1.30e-25	**0.0630**	9.30e-53	**0.0620**	3.90e-51	**0.0143**	0.0015