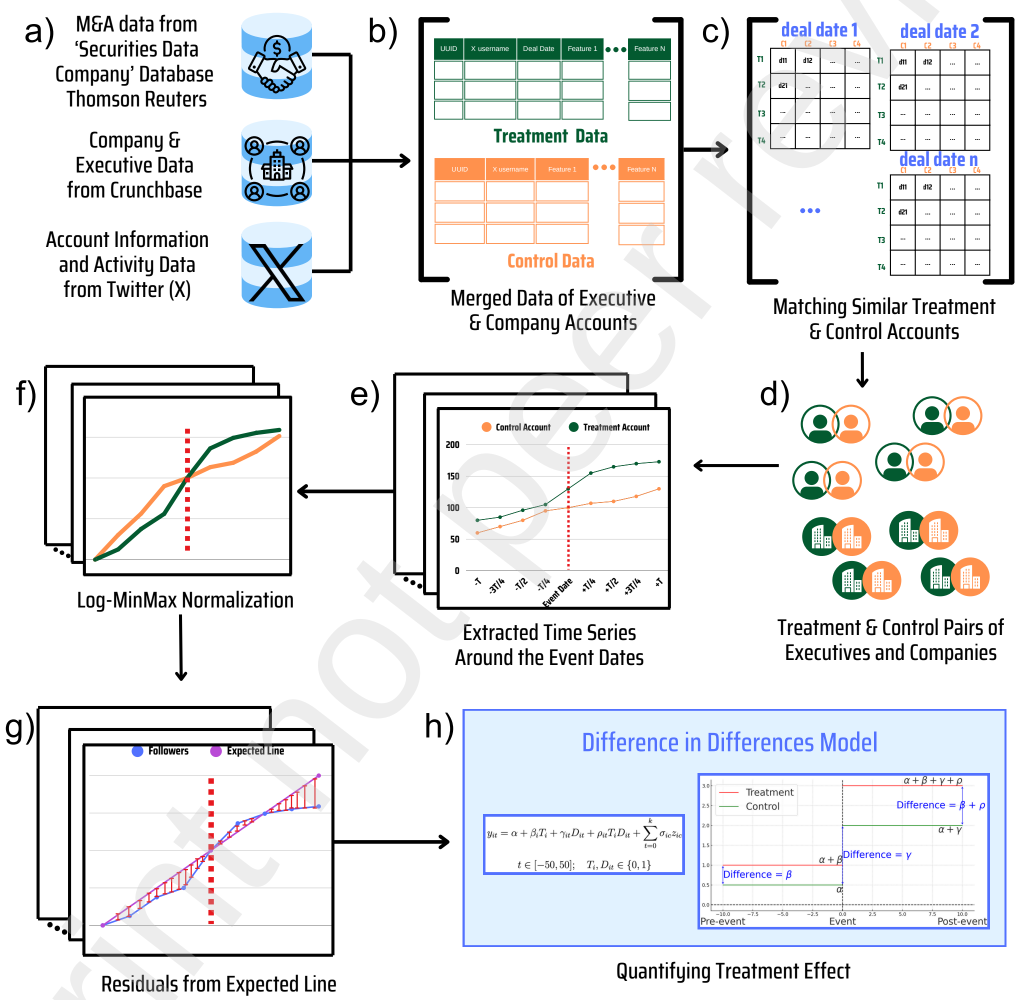
# Graphical Abstract

## Quantifying Effects of Company Mergers and Acquisitions on Online Social Networks

Aysegul Rana Erdemli, Seyma Gozuyilmaz, Onur Varol, Serif Aziz Simsir



## Highlights

**Quantifying Effects of Company Mergers and Acquisitions on Online Social Networks**

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- We study M&A effects on companies' and executives' social media (specifically X) presence.
- Company accounts show stronger reactions than executive accounts after M&As.
- Targets gain more followers and public engagement; acquirers post more frequently.
- Deal quality (CAR) and ownership types of companies (public/private) shape post-announcement social outcomes.
- Difference-in-Differences models are used to isolate how major corporate events shift social media dynamics.

# Quantifying Effects of Company Mergers and Acquisitions on Online Social Networks

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## Abstract

Mergers and Acquisitions (M&As) provide companies opportunities to enhance efficiency, grow, and strengthen competitiveness while affecting a broad set of stakeholders. Given its reach and influence, social media offers a powerful lens for studying such events. While prior work has used social data in financial contexts, there remains a significant gap in understanding how M&As resonate on the X (formerly Twitter) accounts of acquirer and target companies and their executives. We address this gap by linking LSEG SDC Platinum, X, and Crunchbase data and estimating Difference-in-Differences (DiD) models to quantify post-announcement changes in number of followers and posts as well as engagement received. Results show that M&A announcements produce significant shifts in social metrics: company accounts react more strongly than executive accounts; targets gain followers and engagement more than acquirer companies; and acquirer companies generally post more frequently after the event. We conducted experiments to examine two different heterogeneity sources. First, segmenting by market-adjusted cumulative abnormal returns (CAR, days –2 to +2) shows that low-CAR deals draw larger follower gains for acquirer companies, whereas high-CAR deals elicit higher engagement for both companies and executives. Second, by

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ownership, Public–Public pairings deliver consistent company-level follower growth, and all ownership types show post-event engagement increases. Frequency of posts rises for most acquirer companies except Private–Private; among targets, only Private–Private increase tweeting. These findings reveal how M&As influence the social media presence of companies and executives, highlighting how deal quality and ownership shape audience reactions. They also demonstrate the value of DiD for isolating the effects of major corporate events in social media data.

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

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## 1. Introduction

Mergers and Acquisitions (M&A) are significant corporate events that allow companies to improve operational efficiency, strengthen their competitive position against rivals, capitalize on economies of scale, and achieve synergies that would be difficult to realize through independent operations [1]. The benefits of business growth through M&As have made this approach popular among corporations. In 2024, global M&A activity reached an impressive $3.5 trillion, highlighting the widespread use of these transactions as a key mechanism for corporate growth, industry consolidation, and strategic transformation across multiple sectors [2]. Beyond these growth benefits, M&A events often trigger substantial changes in a company's operations and strategic priorities, affecting a wide range of stakeholders.

Acquiring companies frequently implement substantial changes to the operations of the merged entity, including modifications to investment, financing, marketing, innovation, and other core business strategies.[2] As a result, M&As, especially those involving large corporations, affect a broad and diverse set of stakeholders, including executives, employees, customers, suppliers, competitors, consultants, regulators, and shareholders. This paper investigates how these potential changes in corporate strategy are reflected on social media, particularly on X (formerly Twitter), when the merger an-

[2]M&A events typically involve two corporations: the one that acquires another, and the one that is being acquired. The acquiring company is referred to as the acquirer, and the company that is subject to that acquisition is called the target. These roles are used consistently throughout this paper.

nouncement is first made public.

These events represent important milestones for companies, and the manner in which they are communicated and perceived by the public is of significant interest. Social media content offers insights into the activities of companies and their executives while also capturing public reactions, enabling us to measure how the M&A event is perceived. Although companies and executives can control the content and frequency of their posts (will be referred as *tweets* in this paper), the number of followers and the engagement their posts generate remain largely beyond their control. Moreover, financial indicators such as stock prices provide information on investors' responses to these announcements for publicly traded companies. To assess the impact of M&A events and the reactions of both the public and the market, we analyzed the temporal patterns of these signals before and after the events.

Causal inference provides a framework for quantifying the effects of external shocks by analyzing collections of treatment and control samples. In this study, we examined social media data from 1,088 companies and 1,607 executives. Using a difference-in-differences (DiD) approach, combined with stratification based on account type (company/executive), company status (acquirer/target), and financial performance, we evaluate the impact of M&A announcements on both corporate and public engagement from multiple perspectives. Our results reveal systematic and quantifiable patterns associated with these events, offering insights into the dynamics and perceived outcomes of M&A activities as reflected in social media discourse.

## 2. Related Work

The rise of social media as a platform for information dissemination has significantly influenced interactions between companies and investors in capital markets. Researchers in finance and data science have examined whether investor interactions via social media can predict future security prices. Studies have developed predictive models to analyze investors' satisfaction with a company's products or services and their sentiment regarding the company's stock as an investment, investigating whether collective mood and sentiment towards a company can forecast stock returns [3, 4, 5, 6, 7, 8, 9, 10], corporate credit rating [11], stock momentum [12], stock volatility [13, 14], companies' earnings surprises [15, 16], and future company sales [17]. Further research has extended this analysis to other securities, such as bonds [18], options [19], and cryptocurrencies [20], while also exploring how social media interactions among investors influence behavioral biases in securities markets [21, 22, 23, 24]. Furthermore, recent studies have applied causal inference techniques with deep learning to improve interpretability of stock trend predictions from financial news [25].

Social media has also created a platform for companies and executives to engage with investors and customers, prompting research into both companies' use of social media as a news dissemination tool [26, 27, 28, 29] and executives' personal social media engagement [30, 31, 32]. Engagement on social media influences how companies are perceived by their investors and customers, reflects trust in management teams, and captures sentiment towards their products and services. These dynamics become particularly salient in the context of M&A transactions, which are among the most consequential corporate events. M&A deals are major corporate events that affect companies, executives, competitors, customers, suppliers, and regulators. Recent studies have examined the implications of companies' or executives' social media activity in the context of these events. Mazboudi and Khalil [33] find that large acquirers are more likely than small acquirers to use Twitter to publicize their merger agreements. Using Twitter as an information-sharing platform helps reduce information asymmetry among investors, thereby mitigating large negative market reactions to merger announcements. However, Jia et al. [34] show that investor activity on Twitter can also amplify the effects of merger rumors, most of which do not materialize, leading to increased volatility in the share prices of merging companies.

Research has also examined the impact of social media activities on merger outcomes. Negative social media sentiment following a merger announcement has been shown to increase the likelihood that the announced merger agreement is subsequently withdrawn [35, 36]. Chen et al. [37] document that higher minority shareholder engagement on social media reduces agency problems in public Chinese companies, preventing managers from undertaking low-quality acquisitions and, consequently, is associated with higher post-merger value for acquiring companies. The social media activity of C-level executives indicates that more active executives and their completed deals lead to higher levels of engagement and reactions on social media [38].

Although most studies on social media provide observational findings, causal inference methods can be applied to social media data when a natural experiment is identified to study the impact of an event [39, 40, 41, 42]. The real-time nature of social media makes it a suitable tool for companies to monitor customers, address their concerns, and track competitors for strategic decision-making [43, 26, 44]. Moreover, reactions to corporate announcements on these platforms offer managers valuable insights, enabling them to evaluate the effectiveness and accuracy of their decisions [36]. Given its reach and influence, social media serves as a powerful channel for companies to publicize major events such as M&As. Despite these dynamics, there remains a notable lack of research on how such significant corporate events resonate on social media following their announcement. This paper seeks to address that gap.

In this study, we investigate changes in company and executive social media activity and public engagement surrounding merger and acquisition announcements. Specifically, we examine how these announcements influence the number of followers companies and executives attract, the frequency of their tweeting activity, and the engagement they receive on X. Our empirical framework estimates the treatment effect of mergers on social media activity using a DiD design for causal inference, a dimension of M&A research that has not previously been examined through social media signals.

## 3. Methods

In this study, we examined changes in the activity and public attention of company and executive X accounts following M&A announcements. This section outlines the methods used in our analysis, and Figure 1 illustrates the various steps of the methodology.

First, we merged three datasets, namely Crunchbase, the LSEG SDC Platinum, and X, and preprocessed the combined data (see Sections 3.1 & 3.2.1; Figure 1a-b). Second, we matched treatment and control entries to establish a valid baseline for assessing the impact of the event on the treatment group (details of the matching process are in Section 3.2.3; Figure 1c-d). Using the dates of M&A announcements as reference time points, we extracted time series data for the number of followers, number of tweets, and daily engagement from X accounts, and normalized the time series data to transform them into comparable scales (as explained in Sections 3.2.2 & 3.2.4; also see Figure 1e-f).

Finally, we computed the residuals between the observed and modeled time series (as detailed in Section 3.2.5; see Figure 1g) and incorporated the processed time series into a DiD model to identify statistically significant changes in the treatment group compared to the control group (see Section 3.3 and Figure 1h).

### 3.1. Datasets

To investigate the effects of mergers and acquisitions on social media, we tracked online activities and collected detailed information about the companies and outcomes of the M&A events by obtaining and harmonizing datasets from various sources.

**Crunchbase** is an online platform that provides high-quality live data, powered by a unique community of contributors, partners, and in-house data experts. The data were retrieved as of October 2021 and include detailed information about companies and their employees. Initially, we collected data for 1,593,672 companies and 1,245,268 employee entries. Crunchbase provides external URLs for those entitles and we extracted links to the social media profiles of companies and C-level executives, along with associated metadata, to enable comparisons across dimensions such as education, gender, and title for executives, and business category and size for companies.

**The Securities Data Company (SDC) database** of LSEG is one of the world's most trusted sources of information on company takeovers. The dataset includes all merger and acquisition activities with announcement dates from 2010 to September 2021, encompassing a total of 43,748 deals, all with values exceeding 10 million dollars. We obtained detailed information for each M&A event, including deal dates, target companies, and acquiring companies.

**X (formerly Twitter)** is a microblogging platform that offers content on a wide range of topics. We collected daily data on the number of followers, tweets, and engagements posted by the accounts of companies and executives obtained from the Crunchbase dataset. To capture attention towards these companies, we also retrieved detailed information on the number of quotes, retweets, replies, and mentions of these accounts (hereafter referred to collectively as *engagement*). In total, data from X accounts for 11,050 companies and 25,873 executives were collected.

### 3.2. Data Preparation

#### 3.2.1. Merging Datasets

To conduct our analysis, we combined information obtained from three different sources and, to ensure the quality of the data and reliability, we applied preprocessing steps at the dataset level (Figure 1a).

We ensured that each entry included in our time series analysis had the following information available: employee count and industry for companies; degree, title, and gender for executives; and X account details with existing account data (followers, tweets, 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 with an M&A event and control indicating there was no such event around the same time as the treatment it was matched with (see Section 3.2.3 and Figure 1b).

The number of companies that had not participated in any M&A deals was lower than the number of treatment companies. To ensure a sufficient pool of control companies for the next steps, we expanded the control data by including companies that had engaged in M&A at some point, provided that the assigned date (from the matched treatment entry; see Section 3.2.3) was at least two years prior to the earliest deal for those companies.

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 and eliminate the possibility of multiple treatment effects. Meanwhile, we retained deals of the same company that occurred in non-overlapping time frames.

### *3.2.2. Time Series Extraction*

We extracted time series from X data to capture activity and engagement changes (Figure 1e). Each tweet contains metadata about users at the time of tweet creation, and we combined the daily statistics of followers, tweets, and engagement, as we were interested in how these metrics change around the M&A events. We analyzed information available 120 days before and 120 days after the event, resulting in a total of 241 time points for each treatment and control company/executive.[3]

Time series for followers and tweets were recorded as the cumulative number of followers and tweet counts of the account, representing a snapshot of each day. Meanwhile, daily engagement data were not directly available in the X metadata, so it was generated by summing the daily counts of different

[3] An exemplary time series for *Tripadvisor*'s X followers is illustrated in Appendix Figure B.3.

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 instance (see Section 3.2.3 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 and updated when a new information received with a tweet. 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 (detailed in Appendix Figure A.1). The inclusion criteria for accounts with respect to the extracted time series required them to be active and to have at least two changes in followers and tweets during the observation period 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 removed dramatic outliers that exhibited sudden, unnatural changes (before or after M&A, that was not immediately after the announcement) possibly due to major platform updates or inorganic activities associated with these accounts. An example of such an outlier is an account that gained over 18,000 followers (a 242.5% increase) in just 5 days. Large changes in followers or bulk deletion of tweets, which can significantly affect our selected social media metrics, may be driven by major company events, including M&As. Nevertheless, we excluded these cases from the analysis because we could not determine whether the extremely large changes in follower counts were caused by the M&A events.

Next, we identified accounts in the time-series data that required exceptionally long consecutive forward or backward filling. Here, "exceptionally long" refers to values above the 85th percentile, calculated separately for company followers, company tweets, executive followers, and executive tweets (see Figure B.2). We removed accounts with a substantial number of filled periods to ensure that the dataset retained more natural patterns and actual values for most dates. The reason daily engagement was not included in this outlier analysis was that, in our collected tweet data, whenever a data point for followers was missing, engagement was missing as well. Therefore, the outliers stemming from the daily engagement analysis would be the same.

### *3.2.3. Matching*

To perform causal inference and quantify the changes observed around M&A events for the treatment group (companies and executives involved in M&A events), we paired each treatment entry with a control entry by matching their attributes (Figure 1c-d). We then applied the same time series analysis to both groups and measured the differences between the treatment and control groups.

The pairwise matching was conducted separately for companies and executives to identify the closest possible control entry for each treatment entry. A key purpose of this matching process was to assign a hypothetical *event date* to the control accounts, which served as the reference point for constructing the time series. After matching, each control entry received the event date of its corresponding treatment entry, and their time series were aligned around this date.

For both executive and company accounts, we extracted features from their X account data. For both treatment and control groups, we considered the number of followers and tweets during the 120 days prior to the M&A event. To estimate average engagement, we considered the time series data from 120 to 150 days before the M&A event. The total engagement for each tweet, calculated from retweets, mentions, quotes, and replies, was aggregated, and the averages were used as the measure of average engagement.

Additionally, *business category* for companies and *gender*, *highest degree*, and *title* for executives were included in the features used in the matching process (definitions of these features are provided in Table C.1).

Since we quantified the impact of M&A events from X activity, it was crucial to match similar types of X accounts as control counterparts for each treatment entry. The dynamic nature of X profiles made the matching procedure more challenging. We were not only matching on static features; we were also aligning the time of the event and the snapshot of features at that particular time. For the control group, we had to consider a different hypothetical event time for each account in the treatment group. We created distance matrices for each event date, where (i) the treatment axis included entries with an event on that date and (ii) the control axis consisted only of controls with available X data on that date that satisfied the condition of having at least two common one-hot encoded features for executives and at least one for companies with the treatment intersection (Figure 1c). Each cell contained the distance between the three-dimensional vectors formed

Table 1: **Summary of Company and Executive Data**: Three columns represent the three stages of data processing and the size of datasets after those operations. *After Merging* refers to dataset combined through unique identifier and eliminating accounts that do not conform with matching criteria, *After Matching Pairs* refers to instances prepared after matching the most similar treatment and control accounts, and *After Outlier Removal* refers to final number of accounts after eliminating outliers. *Control Total* in the first column represents the control accounts that are not categorized as target or acquirer prior to the matching process. *Control Total* in the other columns are 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 | 341 |
| **Control Total** | 1669 | 1015 | 731 |
| **Total (Companies)** | 2543 | 1851 | 1365 |
| | **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 |

from account size, tweet count, and average engagement for the treatment and control entries. Because these features are time-dependent, we used the event date of the intersecting treatment to calculate the control's features.

After creating the distance matrices for each date, the Hungarian algorithm [45] was used to find the best pairings within each matrix by minimizing the distance. Following the matching procedure, pairwise differences in feature vectors were calculated and outliers with large distances were eliminated to ensure strongly similar treatment-control pairs (see Figure C.5).

Table 1 summarizes the change in data volume during the preparation process. Ultimately, we retained 1,088 unique companies and 1,607 unique executives, resulting in 1,365 company entries and 1,898 executive entries used in the analysis. The number of entries exceeds the count of unique companies and executives because a company or executive could appear multiple times across different periods if they met the inclusion criteria defined in Section 3.2.1.

*3.2.4. Normalization*

In the extracted X time series data, followers, tweets, and engagement were represented as raw numbers, with followers and tweets recorded as cumulative snapshots of each day. Because X accounts varied widely in size, often spanning multiple orders of magnitude, the raw data were normalized to standardize the analysis (Figure 1f). First, a base-10 logarithmic transformation was applied to all values across the time points. Second, a slightly modified min-max normalization was performed. To avoid potential information leakage from future events, the minimum and maximum values were calculated using only the time series data prior to the event, and the normalization was then applied to the entire series using these values.

*3.2.5. Residual Analysis*

To investigate the differences between treatment and control groups in terms of deviations from an account's expected activity trend (defined as the trend before the event), residuals of the normalized time series were calculated (Figure 1g). First, the natural trend for each entry, denoted as the expected line, was determined using a linear equation based on the first and last points prior to the event. Next, the expected value at each time point was computed according to this line. Finally, the residual time series were obtained by calculating the deviation from the expected trend for each entry, specifically by subtracting the expected value at each time point from the actual normalized value of the day.

*3.3. Estimating Average Treatment Effects*

To quantify the impact of M&A events on social media, we employed a linear regression model to estimate the treatment effect using a Difference-in-Differences (DiD) approach (Figure 1h).

$$y_{it} = \alpha + \beta_i T_i + \gamma_{it} D_{it} + \rho_{it} T_i D_{it} + \sum_{t=0}^{k} \sigma_{ic} z_{ic} \tag{1}$$

$$t \in [-50, 50]; \quad T_i, D_{it} \in \{0, 1\}$$

In Equation 1, $y_{it}$ denotes the residual value at time point $t$ in an account $i$'s time series, which can represent followers, tweets, or daily engagement. $T$ is a binary indicator specifying whether the account belongs to the treatment or control group, with $\beta$ as the treatment coefficient capturing 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 $\gamma$ measures the difference between time points before and after the event for the control group. The interaction term $T \times D$ has coefficient $\rho$, which quantifies the effect of the event on the treatment group relative to the control group. The vector $z_{ic}$ includes control variables such as employee count, and one-hot encoded categories for companies, and one-hot encoded categorical features (title, highest degree, gender) for executives, along with account size and time components (year, month, day) for both groups (Table C.1). We also examined alternative specifications of $y_i$, including percent changes relative to values 7 days prior (e.g., $tweet_{i,t}/tweet_{i,t-7} - 1$), with results presented in the Appendix (Figure D.17 and Figure D.18).

Since we are confident that matched control and treatment pairs consist of similar X accounts and share non-time-dependent features, in an ideal scenario there should be no significant differences between the two groups (treatment and control) before the event. Similarly, the control group should not exhibit significant changes after the event date if the event does not affect them. Therefore, neither $\beta$ nor $\gamma$ should be statistically significant in the baseline scenario. However, if merging companies engage in activities not undertaken by control companies (such as strategic timing of other events just before merger announcements), or if merger announcements influence rival companies included as controls, $\beta$ or $\gamma$ may show statistically significant coefficients.

The coefficient $\rho$ being statistically significant and large in magnitude relative to the other coefficients would indicate that the event caused a major change in the treatment group but not in the control group. Therefore, our main hypothesis is that $\rho$ should be significant in most analyses, as M&A events are important occurrences likely to influence X activity and public attention for both companies and executives.

An essential assumption of the DiD design is the parallel trends assumption, which posits that in the absence of an event, the treatment and control groups would have followed similar trends over time. To assess this assumption, researchers typically use both visual and statistical analyses of pre-event trends. A common visual method involves plotting the average values of the outcome variable ($y$) over time for both groups to verify that their trends are reasonably parallel before the event [46]. In our study, Figure 2 shows a reasonably parallel trend in the residual time series for the treatment and control groups prior to the event.

To further evaluate the parallel trends assumption, we computed the slopes of the pre-event trends for individual time series using linear regression. Supplementary Figures D.9 and D.10 show that the overall distributions of treatment and control slopes for log-transformed time series values are similar, with the distribution of slope differences between treatment and control pairs centered around zero. Furthermore, statistical tests indicate that except for one analysis group, acquirer executives, which produced insignificant results in the DiD analysis, there are no statistically significant differences between the pre-event slopes of the treatment and control groups for any of the time series variables.

These findings provide empirical evidence that the treatment and control groups show parallel trends prior to the event date, thereby supporting the assumption required for the reliability of the DiD design.

## 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 in followers, tweets, and daily engagement of 1,365 company and 1,898 executive records. 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.

### *4.1. Social Media Activity Around M&As*

We derived the residual time series for daily engagement, cumulative followers, and cumulative tweets around M&A events for each company and executive 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 the 241 day-long time series and plotted them for the treatment and control groups as shown in Figure 2.

The impact of M&A events on residual activity and engagement, representing deviations from the estimated trend, is more pronounced for companies compared to executives. This distinction is illustrated by the clearer separation between treatment and control group mean residuals in Figures 2a-c for companies versus the more overlapping confidence intervals for executives in Figures 2d-f. Notably, the larger increase in the number of tweets by companies after the event, shown in Figures 2c and 2f, suggests that company accounts tend to tweet more frequently post-announcement compared to executive accounts. Additionally, since M&A announcements typically highlight company names prominently, it is expected that company accounts experience greater gains in followers and higher daily engagement than executive accounts following such events.

Among the three types of metrics, number of followers, number of tweets, and daily engagement, the number of followers captures the most potent and permanent impact of the M&A event, followed by tweets and engagement as shown in Figure 2a and Figure 2d. Tweeting about the M&A or becoming more active on social media after the event naturally leads to an increase in the number of tweets, illustrated in Figure 2c and Figure 2f, while daily engagement may rise accordingly as more tweets typically result in higher engagement, shown in Figure 2b and Figure 2e. The lasting impact on followers is also expected, as M&A events attract public attention to the company and permanently increase its visibility.

### *4.2. Quantifying Treatment Effect*

This section presents the results of the Difference-in-Differences (DiD) model described in Section 3.3. The target variable in the linear regression model, $y_{it}$, represents the number of followers, tweets, or daily engagement of account $i$ at a given time point $t$. To capture the changing effect of the event over time, we utilized multiple post-event time frames as alternative settings. We also conducted additional robustness checks using different pre- and post-event windows, alternative feature sets, and $y_{it}$ values other than residuals, such as week-over-week differences of the three metrics employed. All robustness checks and supplementary results are provided in the Appendix Appendix D.1.

The results presented in Figure 3 and Figure 4 illustrate the statistical significance of the pre-event treatment coefficient $\beta$, dummy coefficient $\gamma$ and interaction coefficient $\rho$ in different analyses. A statistically significant and higher magnitude of $\rho$ 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 explained in Section 3.3.

#### *4.2.1. Companies*

Statistically significant and positive $\rho$ values (Figure 3a and Figure 3d) indicate that both acquirer and target companies gain followers following M&A events, with the effect noticeably stronger and more persistent for target companies. Specifically, target companies experience higher $\rho$ values over a longer period (Figure 3d), suggesting they attract a more sustained increase in followers compared to acquirers (Figure 3a).

Both acquirer and target companies also tend to tweet more frequently after the announcement (Figure 3c and Figure 3f). However, this increase is more sustained for acquirers, as target company accounts often become inactive post-merger due to delisting or integration into the acquiring company's accounts.

Social media users significantly increase their engagement with both acquirer and target companies immediately after the M&A event, as demonstrated by high and statistically significant $\rho$ values (Figure 3b and Figure 3e). While target company accounts initially attract greater attention, public interaction with both acquirers and targets gradually diminishes over time.

Our main analysis focuses primarily on $\rho$ coefficients, as they represent the causal impact of the event. However, we briefly acknowledge the role of $\beta$ and $\gamma$. Significant negative $\beta$ values (Figure 3b) indicate that acquirer treatment accounts attracted slightly less public attention compared to controls prior to the event. Conversely, positive significant $\beta$ values (Figure 3e and Figure 3f) show the opposite pattern for other account types. Additionally, $\gamma$, which captures shifts in the control group's trend post-event, gradually increases over time (Figure 3a and Figure 3f). Nevertheless, these statistically significant $\beta$ and $\gamma$ coefficients are relatively small in magnitude and reflect imperfect matching from the optimization process used for pairing treatment and control groups.

#### *4.2.2. Executives*

Models based on executive data produced less significant $\rho$ values compared to those using company data, suggesting weaker treatment effects for executives' accounts.

Figure 4d shows an immediate increase in the number of followers for target executives, which continues to grow over the subsequent 50 days before gradually declining, as confirmed by robustness models examining a longer post-event period (Figure D.12). Acquirer executives also gain followers within the first five days following the announcement, although this increase is smaller and less persistent (Figure 4a). An instant and notable increase in tweets posted by acquirer executives is evident after the event (Figure 4c); however, no significant change in posting frequency occurs for target executives (Figure 4f). On the other hand, target executives experience a noticeable rise in public attention and daily engagement (Figure 4e). Although their tweet frequency remains unchanged, the heightened engagement suggests that the increased visibility of target executives stems from the announcement itself rather than their own social media activity.

Interestingly, Figure 4b highlights the significance of $\gamma$, representing changes observed within the control group in response to the event. Given that the control group comprises executives comparable to those in the acquirer treatment group, we can speculate that the announcement might generate expectations among competitors regarding similar future deals, thereby increasing public interest toward comparable executives.

### *4.3. Subsample Analysis*

Beyond our baseline analyses on general acquirer/target and company/executive groups, we conducted additional tests by segmenting the data based on two key characteristics: i) the stock market reaction to the acquirer's stock immediately following the M&A announcement, which serves as a proxy for deal quality for the acquirers, and ii) the public or private status of the merging companies. These subgroup analyses allow us to examine whether specific types of M&A deals or company profiles are associated with notably different patterns of social media engagement and activity.

#### *4.3.1. The Role of Acquirer Deal Quality*

To examine the relationship between X engagement and activity and acquirer stock performance, we segmented acquiring companies and their executives based on the magnitude of their Cumulative Abnormal Returns (CAR) around the M&A event. The CAR was calculated as the percentage change in the adjusted acquirer's stock price from two days before to two days after the deal announcement (-2, +2 days). The adjustment was made by subtracting the S&P500 index market return from the acquirer's stock return over the same period. High acquirer CARs indicate investors' confidence in the deal; if the deal represents a good investment for the acquirers and is consummated on attractive terms (e.g., low acquisition price), the market reacts positively to the merger news. Conversely, if investors believe the deal is not economically sensible for the acquirer (e.g., overpayment for target shares), they respond negatively, leading to negative acquirer CARs.

Acquirers are divided into terciles (low, moderate, high) based on their CARs. DiD models are then run separately for the top and bottom tercile groups. Figures 5 and 6 present the estimated $\rho$ coefficients for companies and executives in the low versus high CAR groups across two alternative post-event windows. For company models, the average acquirer CAR is -8.52% for the low CAR group and +13.4% for the high CAR group; for executives, the average CAR is -13.8% for the low group and +11.01% for the high group. These figures indicate that deals were highly successful for the high CAR group but considerably unsuccessful, at least in the short term, for the low CAR group.

Figure 5 illustrates the estimated $\rho$ coefficients from the DiD model for value changes among acquirer companies and acquirer executives, segmented by acquirer CARs. The post-event window in this analysis spans 0 to 10 days.

Interestingly, companies with low CAR values that reflect a negative market response exhibit larger increases in followers compared to those with high CAR values typically associated with positively received deals. This finding suggests that less favorable or more controversial M&A announcements may generate greater public attention on social media, possibly due to heightened scrutiny, speculation, or broader media coverage. In contrast, deals perceived as successful by the market receive less online engagement, perhaps because they align more closely with expectations and generate less debate or surprise. For acquirer executives, the pattern diverges from that of corporate accounts. Both high and low CAR groups exhibit slightly negative $\rho$ coefficients, but these coefficients are not statistically significant for either group.

The second part of Figure 5 shifts the focus to daily engagement metrics such as mentions, retweets, quotes, and replies on posts by acquirer companies and acquirer executives, again segmented by acquirer CAR levels. Here a markedly different pattern emerges. Companies in the high CAR group exhibit substantially higher $\rho$ coefficients. This indicates a strong uptick in user interaction following deals that the market views favorably. In contrast, the low CAR group shows considerably lower engagement effects. These results suggest that highly successful deals, that is those with a high CAR, tend to elicit more active engagement from users.

The analysis on acquirer executives shows a similar pattern in daily engagement. The executives in the high CAR group indicate a meaningful increase in social media interactions following positively perceived M&A announcements. Conversely, executives with low CAR values demonstrate much smaller engagement effects. This alignment between company and executive level engagement suggests that the market success of a deal is reflected not only in corporate communications but also in the personal social media presence of key individuals involved.

Finally, the right hand graph in Figure 5 reveals a somewhat different dynamic for the account holders' tweeting activities after merger announcements. For acquirer companies, the high CAR group shows no change in the frequency of tweets following positively received deals. Although acquirers with low CAR values exhibit a modest increase in such formal communications, this effect is not statistically significant.

Among acquirer executives, the pattern post-announcement is more negative. The executives in the low CAR group show slightly declining tweets, whereas those in the high CAR group show a more noticeable decline. This suggests that following highly successful deals, executives may reduce the frequency of tweets or formal discourse on social media, possibly shifting their focus towards other types of engagement or communications.

We also investigated the impact of M&A announcements on acquirer social media use in the longer term, where the post event window is defined as (0–50 days). Figure 6 reveals a shift in dynamics compared to the short term results. The acquirers in the low CAR group experience more notable increases in followers in the long run, whereas high CAR companies experience a decrease in the number of followers. This pattern reinforces the earlier suggestion that M&A deals perceived less favorably by the market may generate sustained social media attention, potentially due to ongoing scrutiny or debate. On the other hand, acquirer executives in low CAR deals tend to see a decrease in their follower base over the extended period. In contrast, executives in high CAR deals exhibit relatively stable follower counts.

The second section of Figure 6 focuses on daily engagement over a longer period from day 0 to day 50. Acquirer companies involved in high-CAR deals experience a more persistent and pronounced increase in user engagement relative to their low-CAR counterparts. This suggests that positively received deals not only capture immediate attention but may also sustain user interaction over time, potentially reflecting ongoing interest, investor optimism, or broader media amplification. A similar pattern is observed for acquirer executives. Executives in the high-CAR group exhibit more robust and enduring engagement patterns compared to those associated with low CAR outcomes. Thus, when the market views a deal favorably, not only the company but also its leadership benefit from prolonged public interaction on social media platforms.

The third section of Figure 6 examines changes in the volume of acquirer tweets over the longer post-event period. The estimated $\rho$ coefficients for both high- and low-CAR groups are negative, indicating a reduction in posting activity compared to their control groups. The decrease is more pronounced for low-CAR companies, suggesting a more cautious or restrained communication strategy following deals that were less favorably received. High-CAR companies also show negative coefficients, but their decline in posting behavior is less severe, indicating relatively more stable engagement compared to the low-CAR group.

For acquirer executives, the $\rho$ coefficients are negative across both CAR groups. Low-CAR executives exhibit a less pronounced decline in posting activity compared to the high-CAR group, which shows a sharper decrease. This pattern suggests that executives involved in less favorably perceived deals may reduce their social media presence more cautiously, whereas those with high CAR may respond differently, possibly due to varying communication strategies or stakeholder expectations.

*4.3.2. The Role of Companies' Public Ownership Status*

Next, we explored whether the public ownership status (i.e., public or private ownership) of acquirer and target companies influenced the observed social media patterns in company and executive X accounts. Each deal was categorized into one of four combinations based on the public or private status of both the acquirer and target companies: *public–public*, *public–private*, *private–private*, and *private–public*. The investor base for public companies is much broader than that of private companies, so the social media impact of announcements by public companies is expected to be larger than that of private companies.

Figure 7 presents the DiD estimates for each pairing. This analysis helps reveal whether social media response dynamics differ depending on whether the involved companies are publicly traded or privately held.

Public–Public pairings exhibit the most consistently significant $\rho$ coefficients for company accounts, particularly in terms of follower growth. Mergers involving two publicly traded companies attract high levels of public attention. Public–Private deals also show relatively high and significant results, indicating that public acquirers buying private targets still command notable engagement, although to a slightly lesser extent.

In terms of daily engagement, all company pairings regardless of their publicity status demonstrate statistically significant increases after the announcement, highlighting a general boost in public attention toward both acquirer and target companies following the M&A events.

Regarding the number of tweets, nearly all acquirer companies show a significant increase in tweet frequency after the deal with the exception of private acquirers targeting private companies. Interestingly, only target companies in Private–Private deals exhibit a significant rise in tweet frequency, possibly reflecting a strategic attempt to leverage the event for visibility. This contrasts with target companies in Private–Public deals, which actually experience a notable decrease in tweeting activity, suggesting a potential communication freeze or transition.

A similar breakdown across executive accounts reveals weaker effects overall but with several noteworthy distinctions. Target executives in Public–Private and Private–Private deals as well as acquirer executives in Private–Private deals experience significant increases in followers, likely due to increased personal visibility following the announcements. In terms of daily engagement, a significant decline is observed for executives of private acquirer companies, suggesting reduced activity or diminished audience response. The only notable increase in tweeting activity is found among acquirer executives involved in Public–Public deals, possibly reflecting more proactive communication when both companies are publicly traded.

## 5. Discussion

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 a significant role in relation to financial events such as M&As. These results highlight how social media activity reflects and potentially amplifies market-relevant information.

Our findings suggest that the effect of M&A events is generally stronger on company accounts (Figure 3) than on executive accounts (Figure 4). This difference likely arises because deal announcements are officially issued in the name of the companies, naturally attracting more public attention to their accounts, whereas executives are comparatively less visible or widely recognized.

Additionally, we observe that the accounts of target companies are more strongly affected by M&A events compared to those of acquirer companies, with the impact being most evident in follower count (Figure 3d) and daily engagement metrics. Notably, target companies do not appear to increase their tweeting activity post-event, suggesting that the heightened public attention is driven primarily by the announcement itself rather than by new content or increased activity on their accounts. In contrast, acquirer company accounts show a significant increase in tweeting activity following the event, indicating a more proactive communication response.

Earlier studies have shown that large acquirer companies and their executives tend to use X actively [33, 38]. 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 target companies. For instance, the company *Trip Advisor* has a large X account, making it highly visible to the public. Thus, *Trip Advisor* gains and loses followers and engagement not only due to financial events but also from non-financial activities or even ordinary tweets (see Figures B.3 and B.4). Large companies frequently participate 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 (Figure 4d and Figure 4e). This may be due to the fact that target companies are the less known party before the deals, and their name becomes more prominent with the M&A announcement, which increases their visibility compared to the executives of acquirer companies (Figure 4b). Among the models involving executives, follower and daily engagement counts of acquirer executives show the most pronounced effect. On the other hand, the number of tweets in acquirer executive accounts demonstrates a notable increase, in line with the findings for acquirer companies.

Although some models yielded statistically insignificant results, our main findings confirm that M&A events affect 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 their companies, which could result in cases where some executives were not present during the M&A event. If the number of such cases is higher than expected, it may lead to an underestimation of the results' significance for executives. Another issue is that features such as *employee count* for companies and *title* or *highest degree* for executives reflect the date the Crunchbase entry was last updated. For instance, if an M&A deal occurred in 2015 but the entry is from 2019, it is highly possible that the features were different back then (e.g., employee count was 50–100 instead of 1,000–5,000). Considering this, *employee count* was not included in the matching features (see Section 3.2.3). While analyzing the Crunchbase records, we found that some companies shared the same Twitter URL. We investigated these cases and discovered that Crunchbase updated the Twitter account of some target companies to that of their acquirer. By manually checking ~500 entries with duplicated Twitter URLs, 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 show that the X accounts of companies and executives are affected by announced M&A deals. Specifically, the most statistically significant effects are observed for followers of target and acquirer companies, tweets of target companies, daily engagement of both acquirer and target companies, as well as followers of target executives and daily engagement of acquirer executives. The approach we used can also be adapted to investigate the impact of other types of financial events.

## Appendix A. Preprocessing

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 A.1.

(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 A.1a). (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 A.1b). After applying these strategies in all three cases, we forward filled the remaining missing values as needed.

## Appendix B. Inclusion and Exclusion Criterion

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 C.1 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 C.5).

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 B.2 highlights outlier cases in consecutive fills within the followers and tweets time series. Since daily engagement data typically had consistent daily records, exclusions based on this criterion were unnecessary.

## Appendix C. Matching

As detailed in Section 3.2.3, pairwise matching was conducted between the treatment and control groups for both companies and executives. This section provides additional insights into the matching process.

Table C.1 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 3.2.3 for details on the distance matrix and its application). Most features underwent straightforward transformations, such as *log10* 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 C.2.

Table C.1: **Variable Definitions** - 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 highest degree of the executive (see appendix for full list of considered highest degree types) | one-hot-encoding |

Due to the limited availability of company entries that had no M&A events while meeting our inclusion criteria (see Section Appendix B), we expanded the control group to include company data from before any M&A event occurred. This addition to the control group, referred to as *controlv2*, allowed us to increase the pool of matched pairs. Figure C.6 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

Table C.2: 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 |

alignment with our analysis requirements.

Figures C.7 and C.8 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 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.

## Appendix D. Methods

### *Appendix D.1. Robustness Analysis Results*

In this section, we present robustness analyses of different difference-in-differences (DiD) analysis results that were not included in the main findings.

For the main results, we used residual time series for followers, tweets, and daily engagement data (see Section 3.2.5). The analysis 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 event. To test the robustness of our findings, additional analysis were conducted under two different scenarios, (i) using different before and

Table D.3: 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 |
| | | Tweets | 0.000353 | 0.000393 | 0.3999 | 0.3811 |
| | | Daily Engagement | 0.000000 | 0.000000 | 0.6849 | 0.3786 |
| | target | Followers | 0.000243 | 0.000269 | 0.6032 | 0.2291 |
| | | Tweets | 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*** |
| | | Tweets | 0.000284 | 0.000291 | 0.3536 | 0.5056 |
| | | Daily Engagement | 0.000000 | 0.000000 | 0.0554 | 0.5149 |
| | target | Followers | 0.000220 | 0.000223 | 0.8195 | 0.8917 |
| | | Tweets | 0.000233 | 0.000229 | 0.3781 | 0.4360 |
| | | Daily Engagement | 0.000000 | 0.000000 | 0.2221 | 0.1836 |

Table D.4: Interpretations of Coefficient Magnitudes and Signs

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

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 D.11 and D.12 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 $\rho$, representing the effect of the event, gradually decreases over time in cases where it was notably significant compared to other coefficients.

Interestingly, there are also instances where the magnitude of $\rho$ 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 D.13 and D.14).

Analysis conducted on various symmetric time ranges before and after the event, as shown in Figures D.15 and D.16, generally produced less significant results.

In addition to residuals, we constructed alternative time series for followers, tweets, 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 analysis conducted on these alternative time series also demonstrated significant results, as shown in Figures D.17 and D.18.

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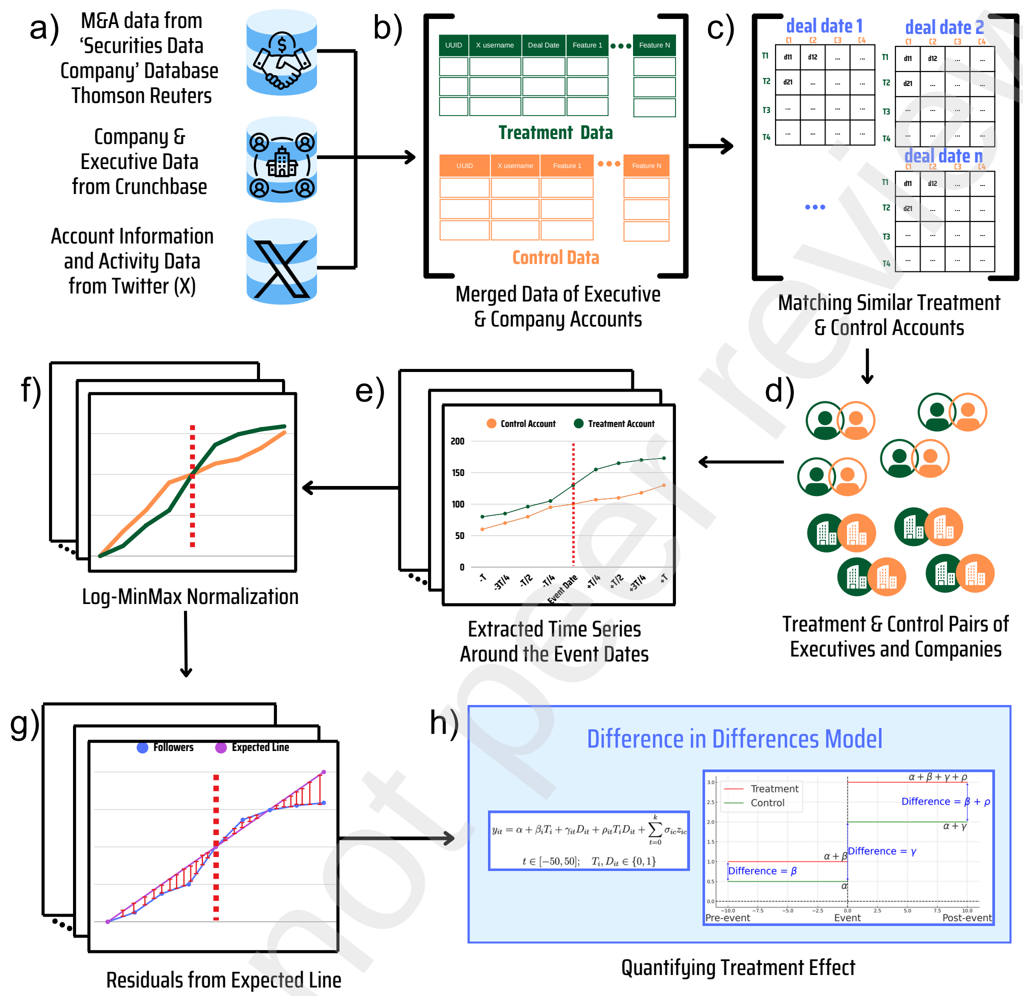



Figure 1: **Schematic overview of the methodology**. Main datasets are merged (a) and divided into treatment and control datasets (b) including information from all three. Similarity between treatment and control samples calculated considering their features at the time of M&As (c) and the most similar pairs are matched for the causal inference analysis (d). Time series around the event dates (-120, +120) were extracted for number of followers and tweets and daily engagement for every entry (e). Logarithmic transformation was applied to time series signals and then min-max normalization was used to standardize each signal (f). Residuals for the time series (deviations from the expected trend line created with the information before the event) were calculated for every entry (g). Finally, DiD model was employed using residual data of followers, tweets, daily engagement for all entries in order to observe the significant change in treatment accounts after the event (h).

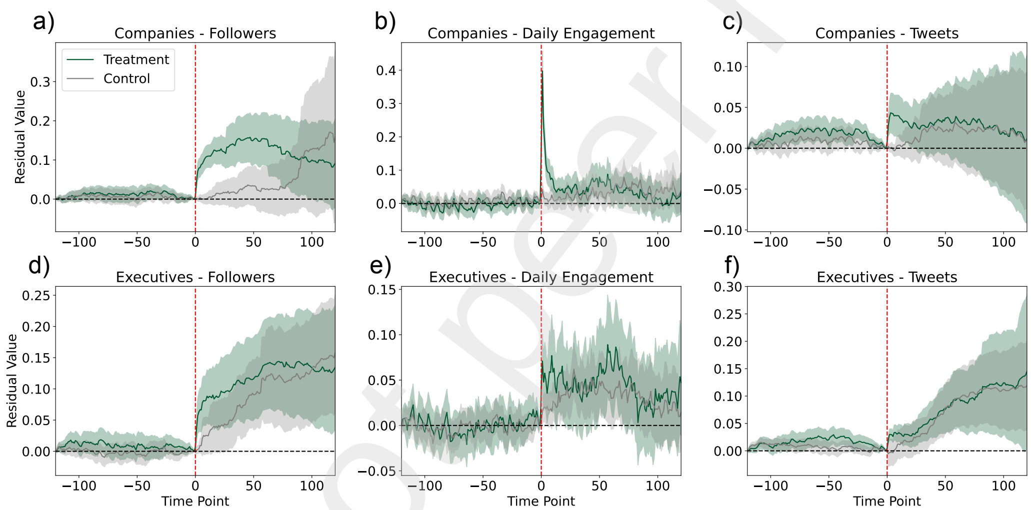



Figure 2: **Treatment Effect**. Mean residuals of change in followers, tweets and daily engagement time series of companies (a, b, c) and executives (d, e, f) demonstrating the difference between treatment and control groups following the event date.

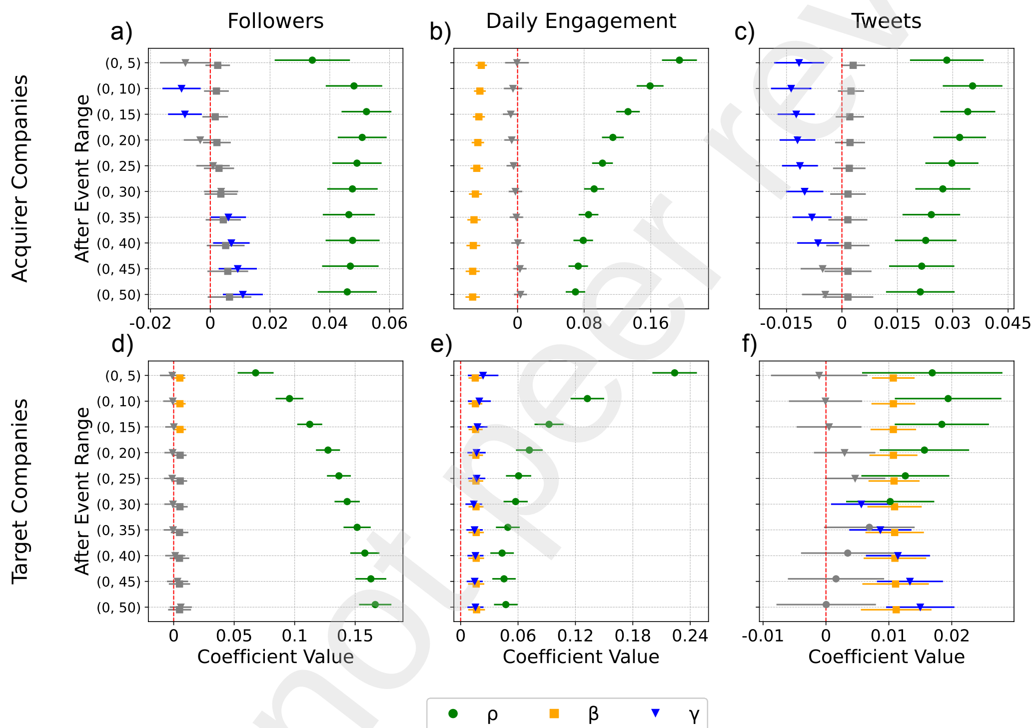



Figure 3: **Model Results - Companies** DiD model results in terms of the magnitude and statistical significance of the key coefficients, $\beta$, $\gamma$ and $\rho$. Statistically significant values of the coefficients are shown in colors and statistically insignificant values are all shown in gray. The pre-event window is constant at (-50, 0) for all models. Results for acquirer (a, b, c) and target (d, e, f) companies are shown in two rows.

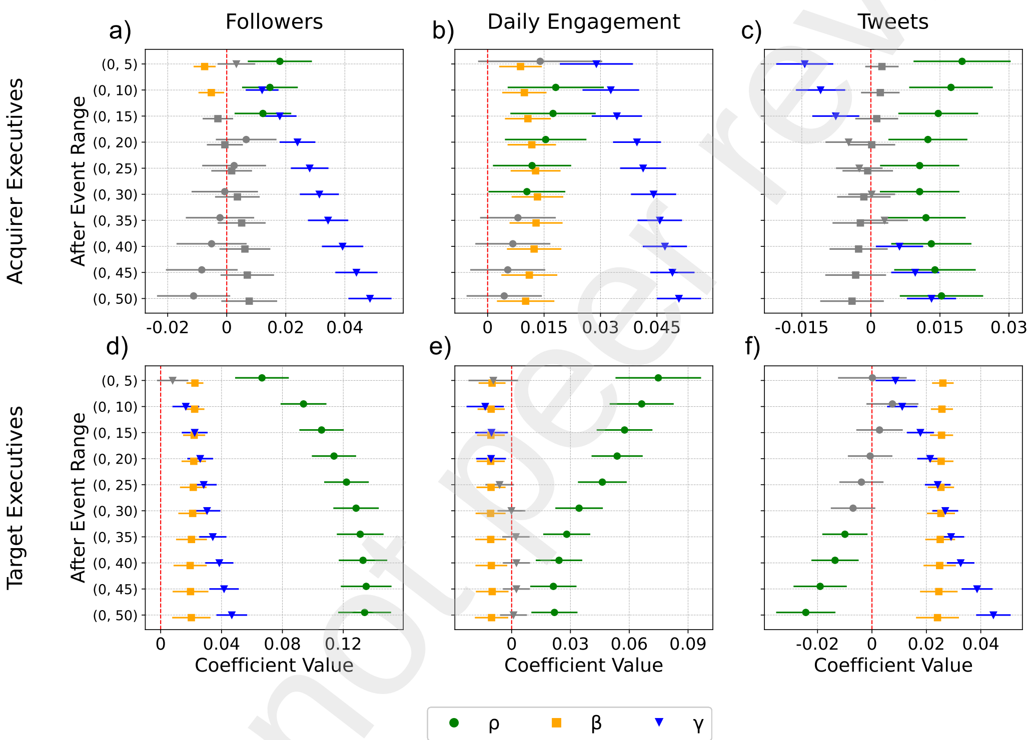



Figure 4: **Model Results - Executives** DiD model results in terms of the magnitude and statistical significance of the key coefficients, $\beta$, $\gamma$ and $\rho$. Statistically significant values of the coefficients are shown in colors and statistically insignificant values are all shown in gray. The pre-event window is constant at (-50, 0) for all models. Results for acquirer (a, b, c) and target (d, e, f) companies are shown in two rows.

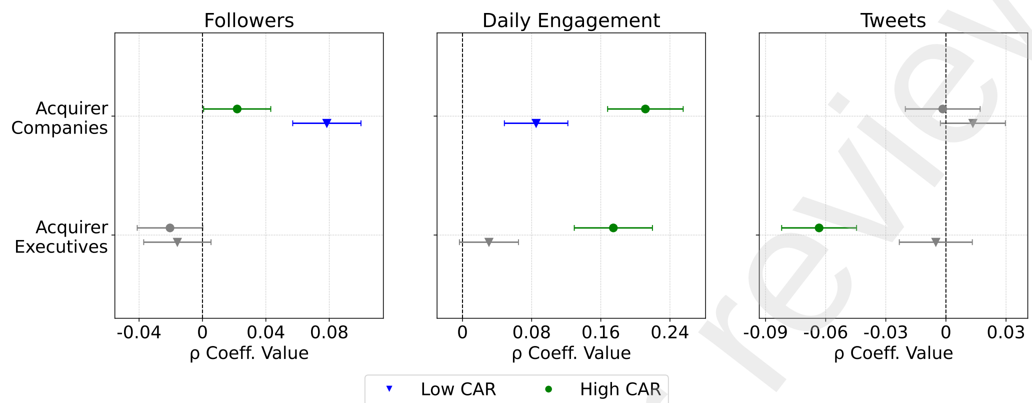



Figure 5: **Model Results by Acquirer CAR Groups (Post-Event Window: 0–10 Days)** — Estimated $\rho$ coefficients from the DiD model comparing acquirer companies and executives across low and high CAR groups. Low-CAR groups are shown in blue, and high-CARs in green. Faded markers denote statistically insignificant coefficients.

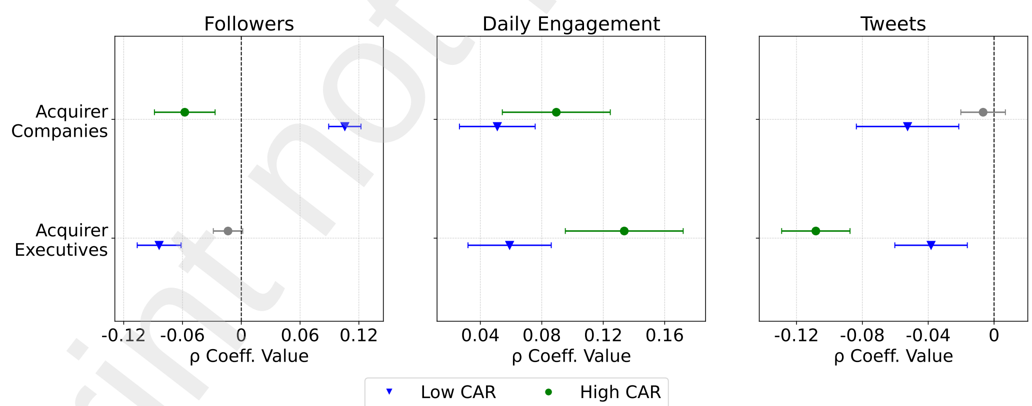



Figure 6: **Model Results by Acquirer CAR Groups (Post-Event Window: 0–50 Days)** — Same analysis as Figure 5, but over a longer post-event window of 50 days. The extended window captures longer-term social media engagement patterns and their association with stock market reactions.

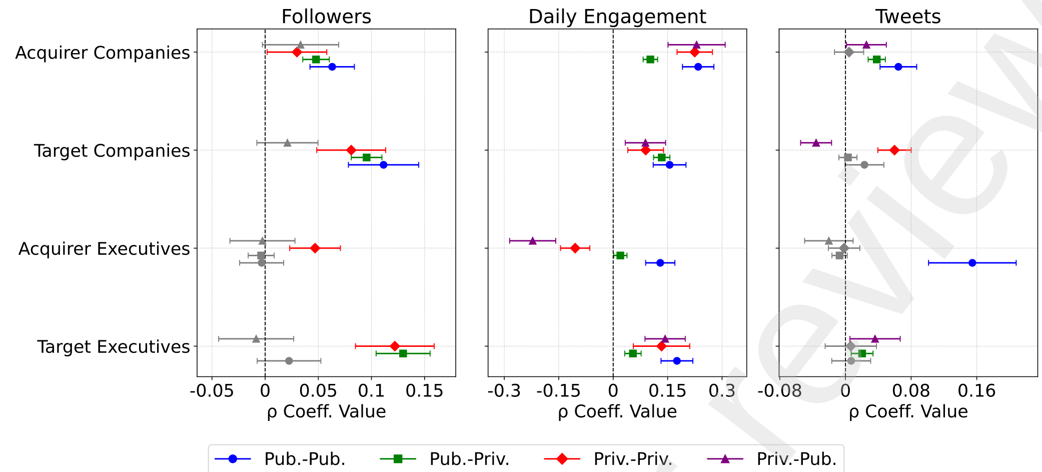
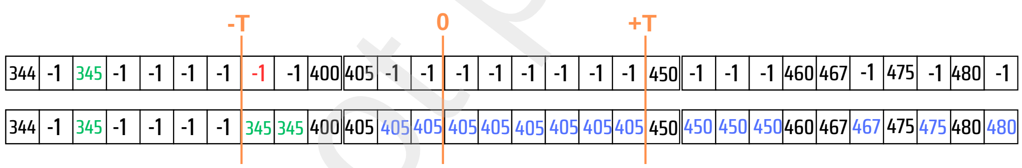
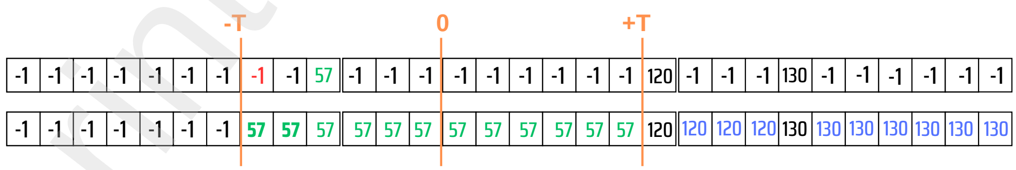



Figure 7: **Model Results by Public/Private Status (Post-Event Window: 0–10 Days)** — Estimated $\rho$ coefficients from the DiD model for different combinations of acquirer and target publicity status. Color-coded lines represent each combination (e.g., Public–Private in green, Private–Private in red). Error bars indicate confidence intervals, and transparency reflects statistical significance.




(a) Forward filling the first indices




(b) Backward filling the first indices

Figure A.1: 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.

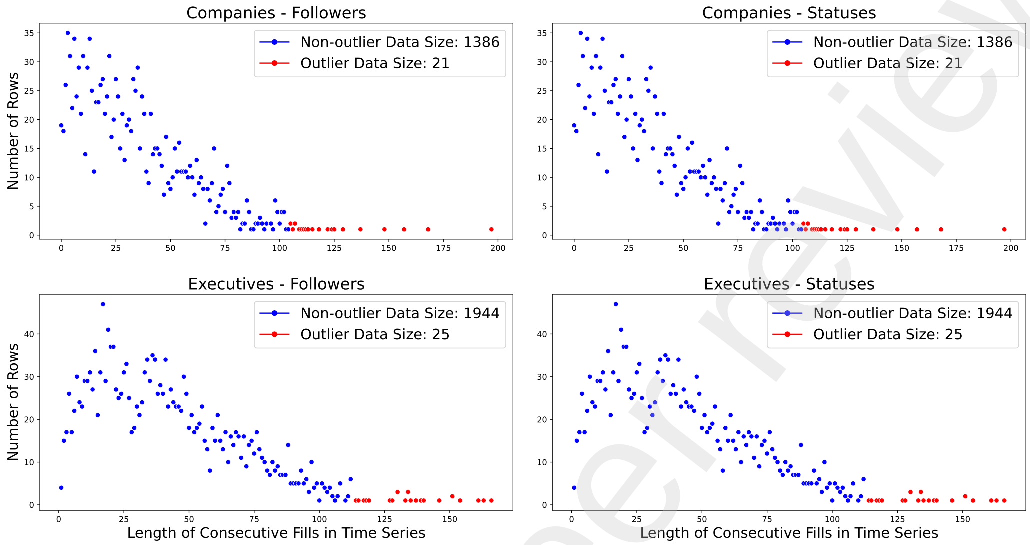



Figure B.2: **Outliers - Longest Consecutive Fills** Outliers in the 85% percentile are colored in red, which are the data where there are very long consecutive series filled with forward-backward filling approach explained in Figure A.1

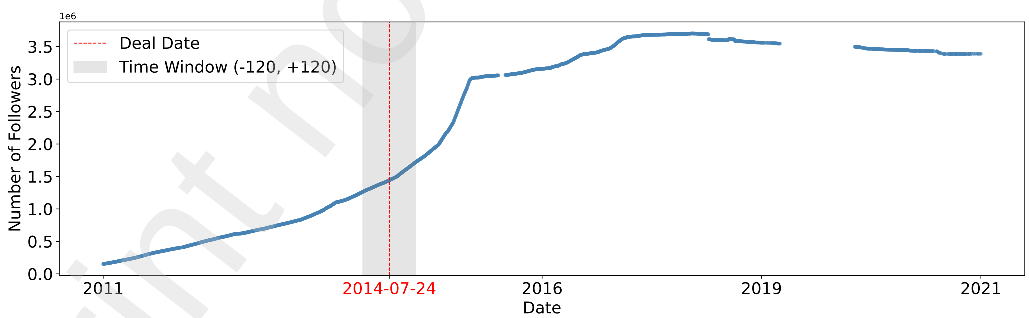



Figure B.3: **Raw Follower Time Series of *Tripadvisor* (Treatment Acquirer)** Cumulative number of followers of Tripadvisor's X account between the years 2011-2021. There are missing data at some dates. Red vertical line represents the deal date of an M&A which Tripadvisor was an acquirer company in. Gray area illustrates the time window we used in our analysis.

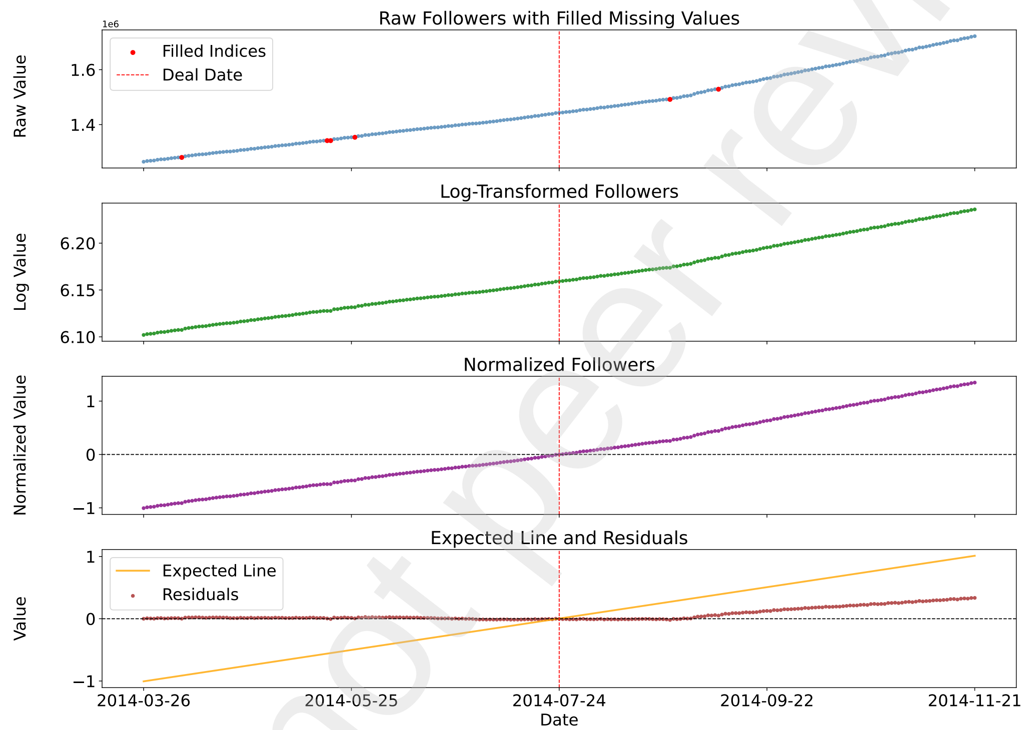



Figure B.4: **Processed Follower Time Series of *Tripadvisor* (Treatment Acquirer)** Transformations and preprocessing applied on raw time series described in Section 3.2. After the extraction of time series around the event date (Figure B.3), missing date values are imputed with forward and backward filling approach (Figure A.1) 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.

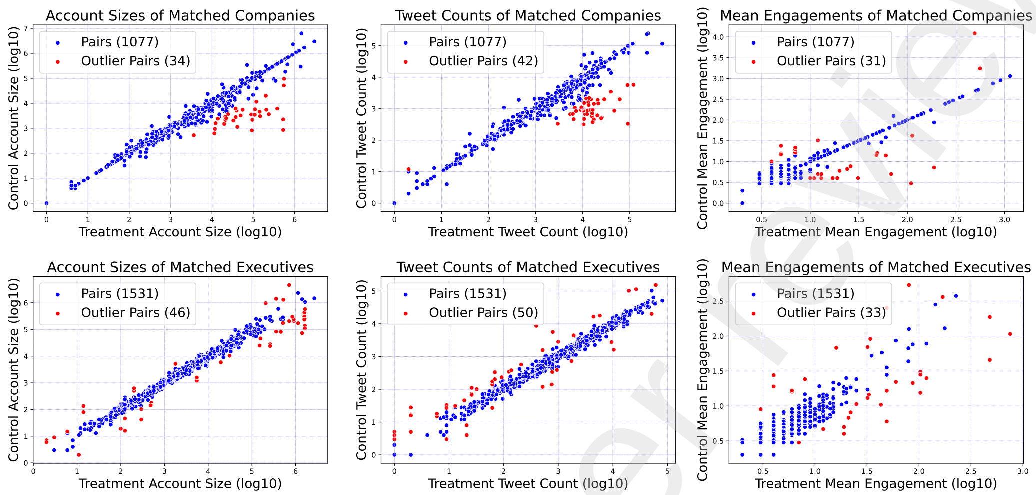



Figure C.5: **Outliers - Feature Similarity in Matched Pairs** Outliers decided with a z-score of 2.5 in terms of the distance from 45° line (indicating a perfect match with no difference between the value of the feature of treatment and control) are colored in red, which are the treatment-control pairs which have a significant difference in on of their X account features.

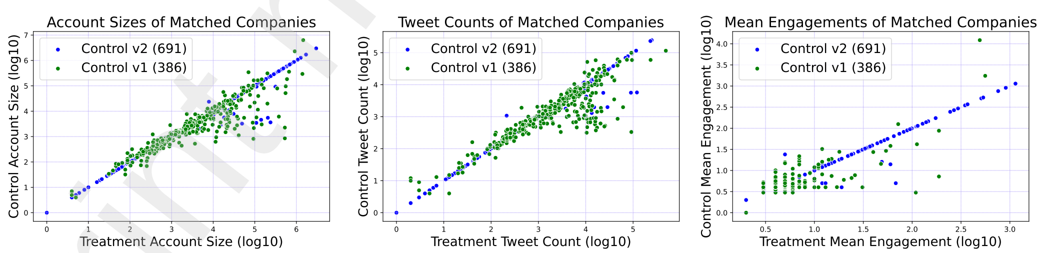



Figure C.6: **Control Types in Matched Pairs** X axis being the treatment and Y axis being the control, individual datapoints represent the difference between matched pairs. Green color indicates treatments matched with original controls while blue color is used to identify the matches with the type controlv2 companies (See Section 3.2.1).

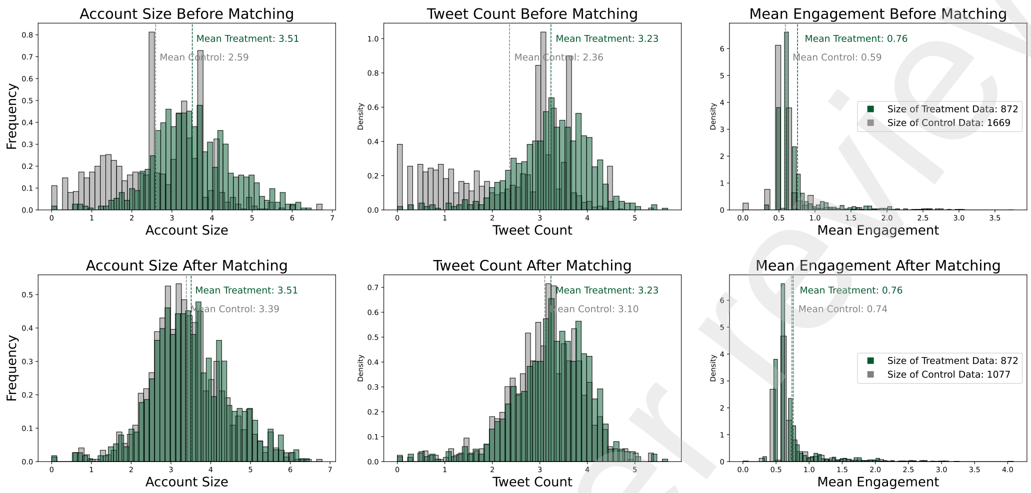



Figure C.7: **Distribution of Features Before and After Pairwise Matching - Companies**

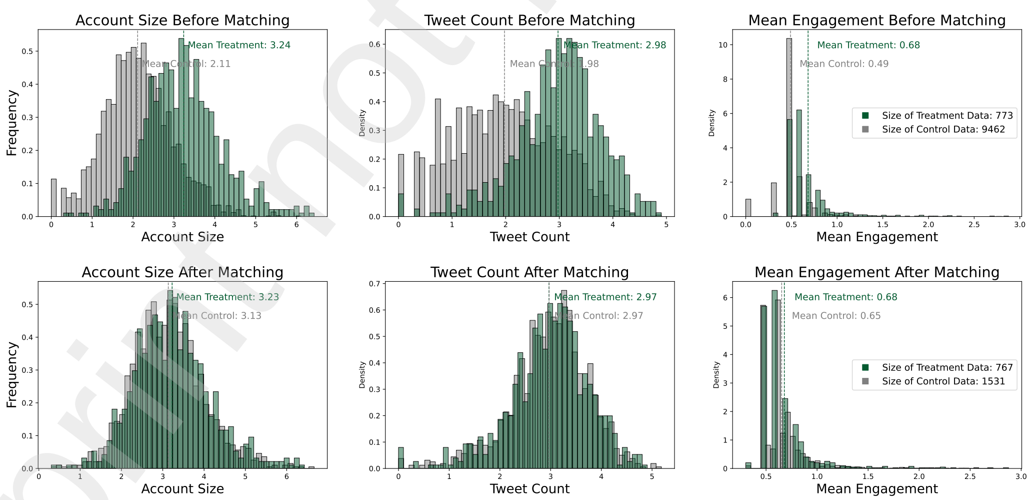



Figure C.8: **Distribution of Features Before and After Pairwise Matching - Executives**

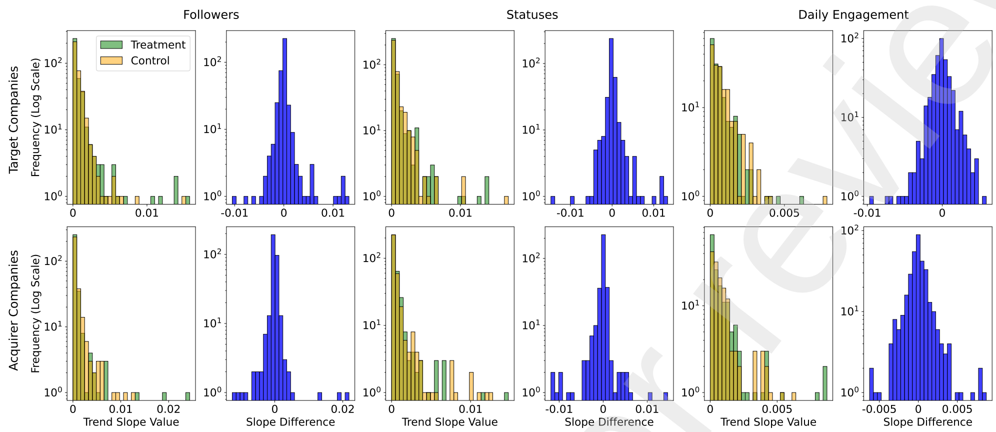



Figure D.9: **Pre-trend Slope Distributions of Companies**

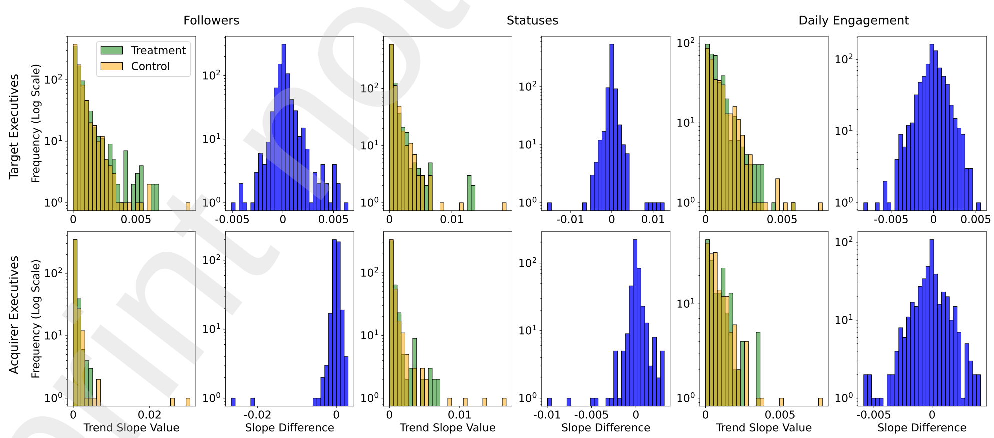



Figure D.10: **Pre-trend Slope Distributions of Executives**

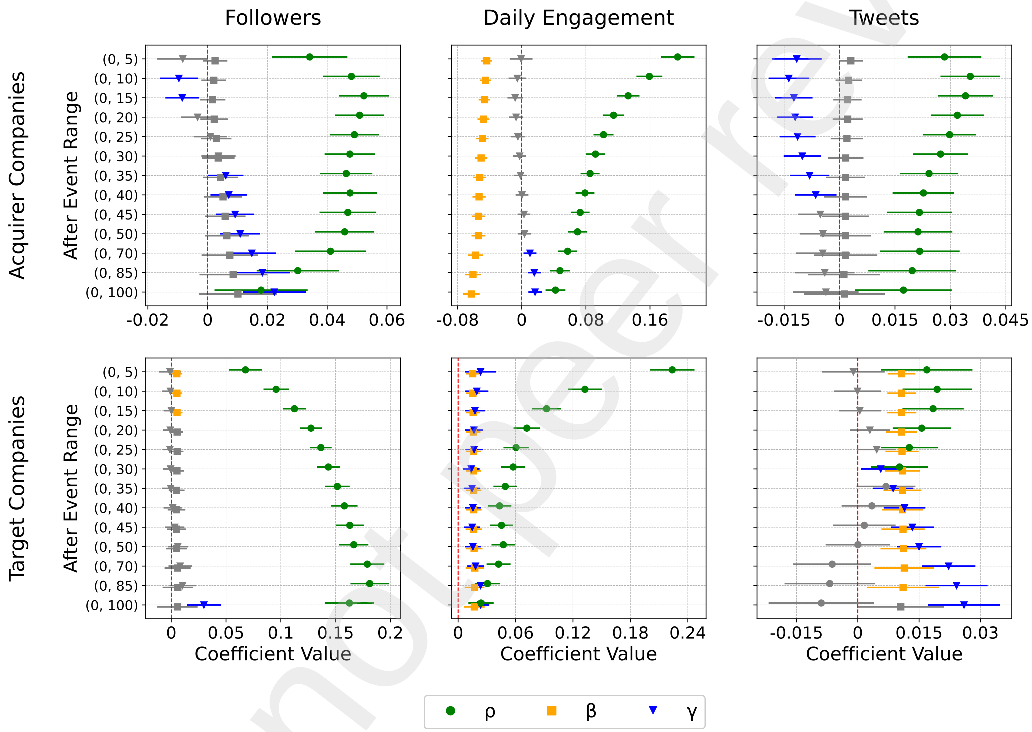



Figure D.11: **Model Results - Different Time Frames Robustness Analysis for Companies** Diff-in-diff model results for companies with different time ranges than presented in the main results (Figure 3). Before time range is constant and (-50, 0) for all analysis. After time range for longer time periods (up to (0, 100) is shown in order to see the long-term effect.

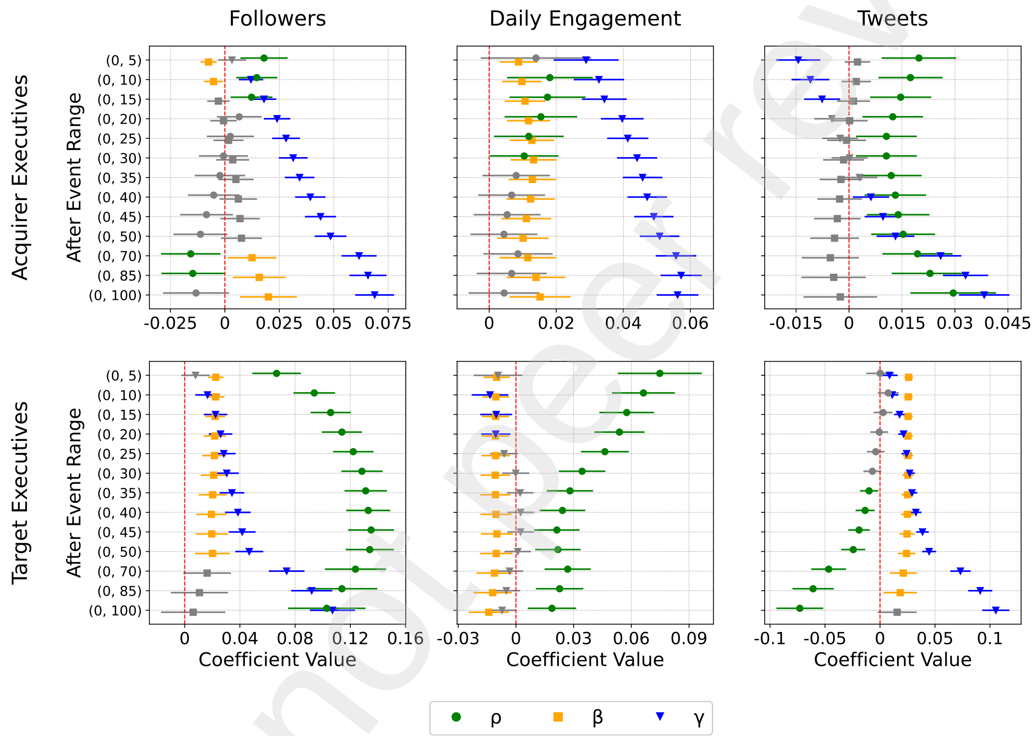



Figure D.12: **Model Results - Different Time Frames Robustness Analysis for Executives** Diff-in-diff model results for executives with different time ranges than presented in the main results (Figure 4). Before time range is constant and (-50, 0) for all analysis. After time range for longer time periods (up to (0, 100) is shown in order to see the long-term effect.

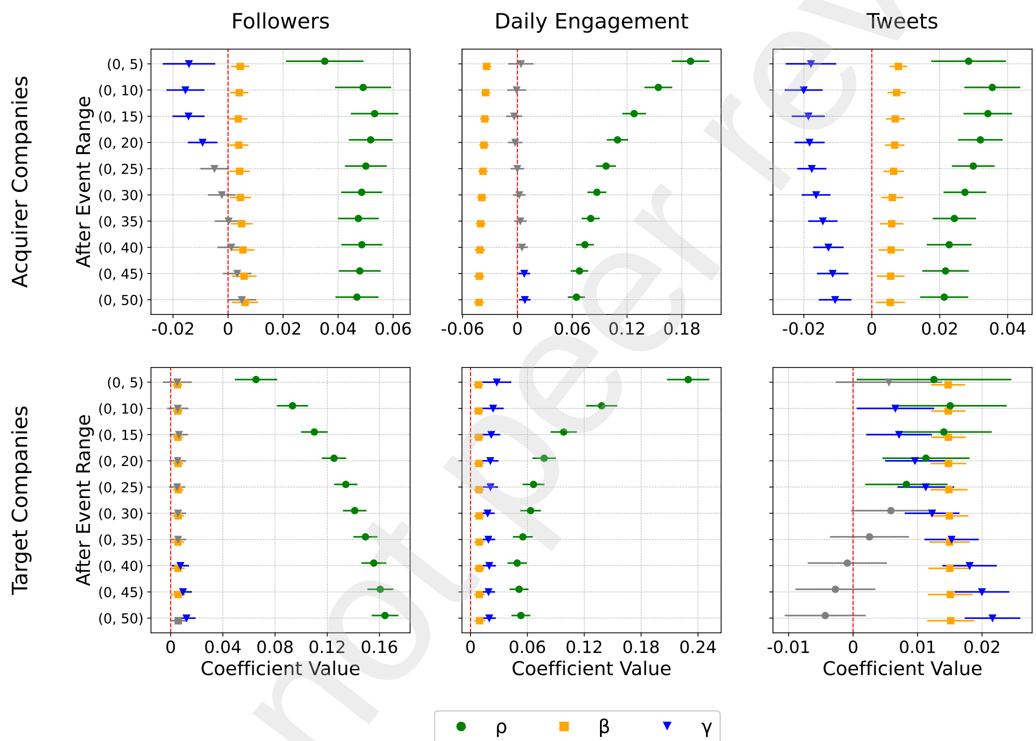



Figure D.13: **Model Results - Different Time Frames Robustness Analysis for Companies** Diff-in-diff model results for companies with different time ranges than presented in the main results (Figure 3). Before time range being constant and (-100, 0), asymmetric after time ranges are used to see the the effect in time.

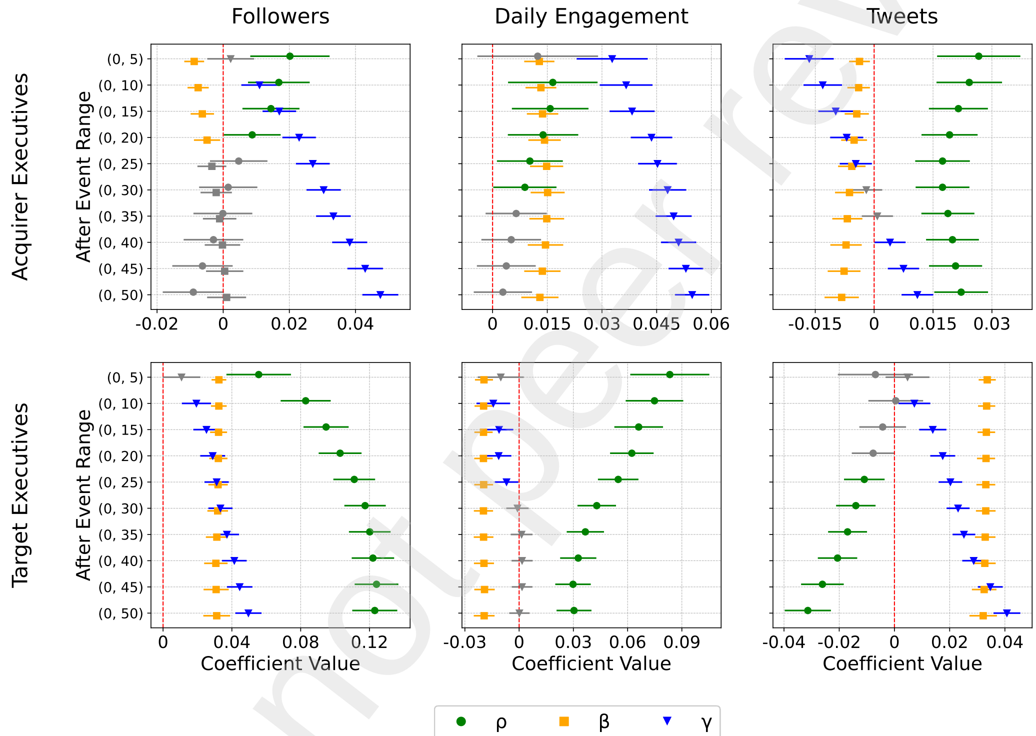



Figure D.14: **Model Results - Different Time Frames Robustness Analysis for Executives** Diff-in-diff model results for executives with different time ranges than presented in the main results (Figure 4). Before time range being constant and (-100, 0), asymmetric after time ranges are used to see the the effect in time.

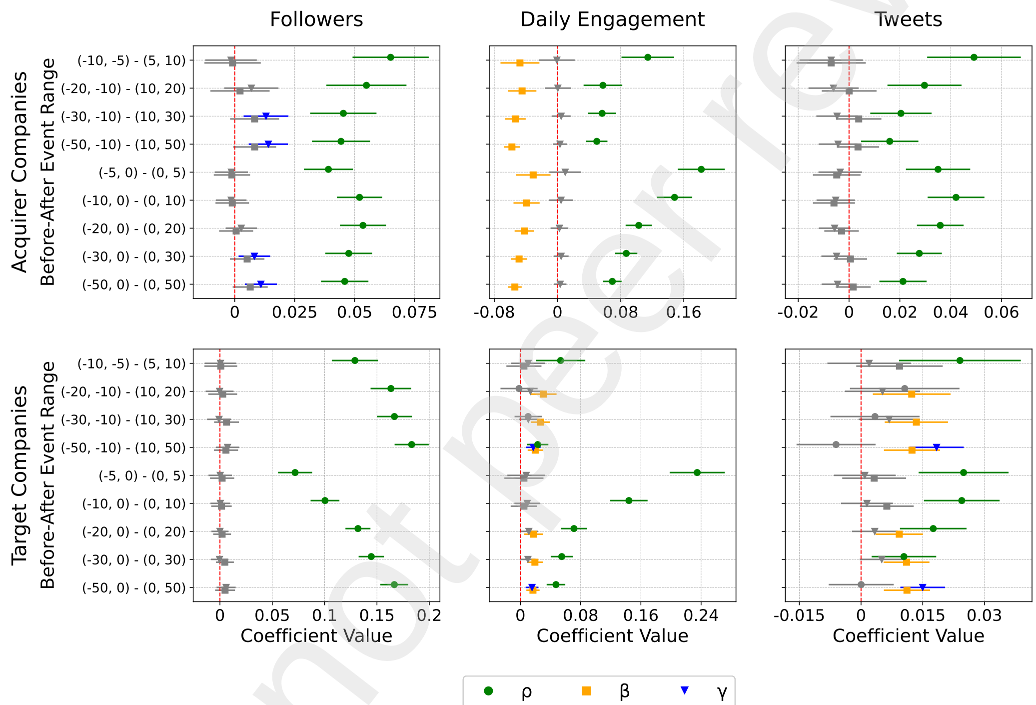



Figure D.15: **Model Results - Different Time Frames Robustness Analysis for Companies** Diff-in-diff model results for companies with different time ranges than presented in the main results (Fig. 3). Symmetric before and after time ranges are used to see the the effect of short and long time periods.

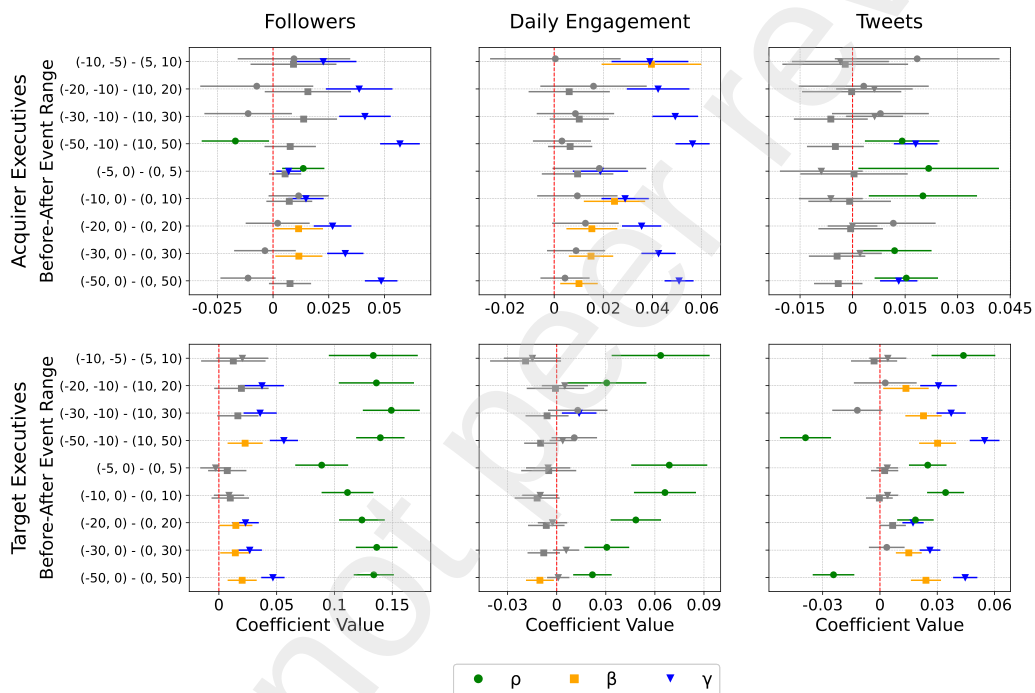



Figure D.16: **Model Results - Different Time Frames Robustness Analysis for Executives** Diff-in-diff model results for executives with different time ranges than presented in the main results (Fig. 4). Symmetric before and after time ranges are used to see the the effect of short and long time periods.

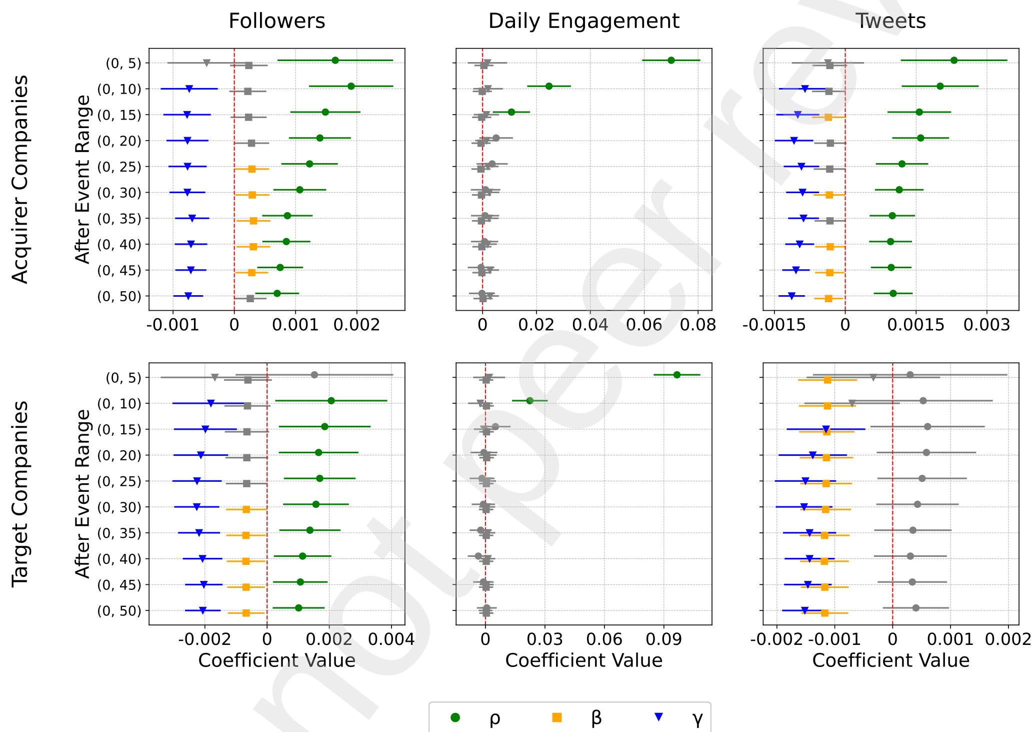



Figure D.17: **Model Results - Different Time Series Values Robustness Analysis for Companies** Diff-in-diff model results for companies with different time series values unlike residuals used in the main results (Figure 3). Every time point is the difference of the normalized value from the 7 day before.

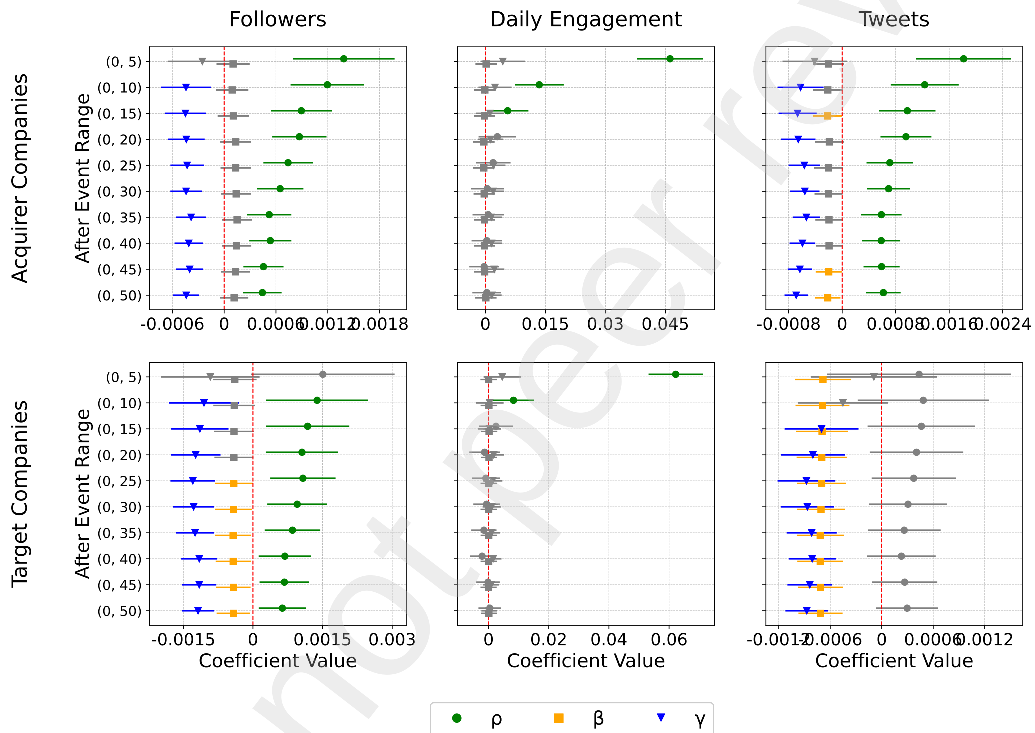



Figure D.18: **Model Results - Different Time Series Values Robustness Analysis for Companies** Diff-in-diff model results for companies with different time series values unlike residuals used in the main results (Figure 3). Every time point is the difference of the normalized value from the mean of the last 7 days.