Distinct outside forces influencing firm outcomes: Social media and city crime

Tahmina Ahmed

PhD Candidate

Schulich School of Business

York University

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Abstract

Business entities face a multitude of external influences such as social, economic, and environmental factors. These outside forces have the capacity to instigate meaningful financial outcomes, emphasizing their importance for both the firms themselves and external stakeholders, namely, investors and regulatory authorities. In my dissertation, I explore two such outside yet discrete forces – social media engagement and city crime. Building on the concept of "online firestorms" that tweets can entice, I investigate a set of tweets sent by the S&P500 firms and their CEOs that the Twitterverse considers controversial. Consistent with social media's cancel culture, I find evidence that the perceived controversial CEO tweets are associated with significant negative stock market reactions. The detrimental impact of CEOs' controversial tweets is intensified for firms with "Star CEOs" and reversed for firms with high individual ownership. Using the same concept of "controversy" in firm tweets, I find contrasting outcomes that imply a positive significant reaction of controversial tweets on the stock market. This evidence complements inferences from previous studies that documented price-distortion behavior of social media messages firms post. Sentiment analyses of these firm-tweets reveal when the tweet contents are positively oriented, the market reacts more optimistically no matter the perceived controversy in the tweets. My dissertation expands the influence of outside forces by investigating crime rate in the city in which firms are headquartered. Using the Accounting and Auditing Enforcement Releases issued by the SEC to firms for fraudulent financial reporting and the city crime rates in the USA, I show evidence that indicates the higher the crime rate in the city in which firms are headquartered, the higher the likelihood of fraudulent reporting. Further, with subsample analysis, I demonstrate a nuanced influence of CEO compensation and of proximity to the SEC's headquarter, on the relationship between crime and fraudulent financial reporting.

Dedication

To my daughter, Daneen Nahwah.

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Chapter One: Introduction

Besides internal and institutional settings, the external environment, such as government regulations and information technology (Armenakis & Bedeian, 1999; Bharadwaj, 2000), has a significant influence on business outcomes (Bruton et al., 2010; Khalid & Rajaguru, 2018; Pfeffer & Salancik, 1978). In my three-paper model of the dissertation, I explore two outside forces that impact firm performance and governance: 1) social media (Cheong et al, 2022; Chen, 2014; Green et al., 2019; Kuhnen & Niessen, 2012; Meadows & Meadows, 2016; Teoh, 2018; Wu, 2004), and 2) crime rates (Botrić, 2021; Hua & Yang, 2017; Motta, 2017).

In chapter one, I investigate public responses on social media. The social media platform Twitter[1] has been shown to impact the stock market significantly. Building on social scientific research on the effects of "cancel culture" and controversial social media messaging, I posit that tweets sent by CEOs that come to be seen as controversial by the Twitterverse have an outsized impact on stock market prices. A key indicator of whether a tweet is controversial – and the core of this study – is when a tweet receives substantially more replies than retweets or likes. When this occurs, a tweet is considered to have been ratioed. This study takes up this idea with a sample of ratioed tweets sent by S&P 500 CEOs to examine whether controversy in CEO tweets influences the markets. Moreover, I investigate whether there is any intensifying effect of CEO stardom and high individual ownership on the abnormal stock returns that controversial CEO tweets generate.

In chapter two, I go beyond examining the main effect of controversy in tweets on stock prices and investigate what makes tweets controversial – *tweet sentiment*. In contrast to chapter one, which looked at CEO tweets, in this chapter I look at tweets sent by S&P 500 firms' Twitter accounts. It is well established in the literature that information posted on Twitter can significantly influence the stock market (Arteaga-Garavito et al., 2020; Blankespoor et al., 2014; Lee et al., 2015) and that the stock response is higher for bad news about firms (Hutton et al., 2003; Kothari et al., 2009; Soffer et al., 2000). Building on the growing literature that examines the two-way dialogue between firms and the Twitterverse (Minot et al., 2021; Saxton et al.,

[1] Twitter is now called X, but to be true to the company name at the time of data collection, and to avoid confusion regarding common terminology for independent variables, I use the term "Twitter" throughout the dissertation.

2021), I first test the annual average controversy level in firm tweets and long-run cumulative stock market returns of S&P 500 firms. I then analyze the sentiment in the tweets to explore whether they influence the relationship between controversial tweets and stock market returns. Additionally, I investigate the impact of controversy in firm tweets around one of the most significant events for a firm, the earnings announcement events.

In chapter three, I examine the association between city crime rates and accounting fraud committed by the firms headquartered in those cities. Crime in society can affect a firm's business decisions (Bates & Robb, 2008; Hipp et al., 2019; Parsons et al., 2018; Sacerdote & Scheinkman, 1996; Sloan et al., 2016). Although not tested for causality, I conjecture that firms and their employees that are more exposed to local crime might be more lenient towards misdeeds (Sacerdote & Scheinkman, 1996) and that, therefore, the likelihood of accounting fraud by the firms located in a crime-prone area would increase. Unlike studies that claim that internal factors within firms such as firm performance, stock performance, dividend policy, and corporate governance determine likelihood of accounting fraud (Bao et al., 2020; Beasley, 1996; Bonner et al., 1998; Brown et al., 2020; Summers & Sweeney, 1998), my paper explores an outside factor of the environment, *city crime* to be specific, as a potential determinant of accounting fraud. I also investigate property and violent crimes separately to show the variation of influences on the likelihood of fraudulent reporting. Further, I examine how the influence of city crime on fraudulent financial reporting differs between companies compensating their CEOs with high and low compensation. Finally, I analyze how the accounting practices of firms are influenced by city crime, specially focusing on subsamples of companies categorized by their proximity to the regulatory body, the Securities & Exchange Commission (SEC).

Chapter Two: Does Controversy in CEO Tweets Influence the Stock Market?

1. Introduction

With the evolution of social media-led business communications, corporations and their CEOs often disseminate news via official accounts on Twitter, a social media platform that has reached around 300 million monthly active users (Iqbal, 2023) and which, despite recent upheavals, remains an influential platform for investors. Social media's built-in liking, sharing, and commenting features allow CEOs to spread the word, build conversations, and engage with core stakeholders (Elliott et al., 2018; Malhotra & Malhotra, 2016). At the same time, CEO messages carry the potential risk of generating negative feedback and creating controversy (Heavey et al., 2020). While existing research has examined the positive side of this equation – such as how CEO tweets can convey significant meaning for the firm (Crowley et al., 2021; Elliott et al., 2018) – the empirical literature has yet to examine the negative side of the equation. What happens, for instance, when a CEO ignites an online "firestorm" by posting a message that social media users find controversial? My study examines whether the controversy level in CEO messages engenders a market reaction.

Besides the broad literature on the relationship between company tweets and stock prices (Bartov et al., 2018; Bilinski, 2022; Blankespoor et al., 2014; Booker et al., 2023; Saxton, 2019; Tang, 2018), studies have documented that tweets sent directly from the CEOs can also influence the stock market (Crowley et al., 2021; Elliott et al., 2018). The effect is due not only to new information (Blankespoor et al., 2020) but also to the social bond with and the trust of the CEOs (Elliott et al., 2018). This suggests that investors would react when CEOs say something controversial. Given CEOs' ability to spark online debates (Heavey et al., 2020) and investors acting on CEOs' tweets (Elliott et al., 2018), I posit that CEO tweets that investors consider *controversial* will spark significant stock market reactions. A standard indicator of whether a tweet is controversial – and the core of this study – is when a tweet receives more replies than retweets or likes. A Data for Progress Report (*The Ratio Richter Scale*, 2023) explains that, as it takes considerably more effort to find, read, and reply to a tweet than just liking or retweeting it, Twitter users are more likely to undertake the effort to reply only when they find the tweet objectionable. Moreover, Alsabah (2024) uses Twitter engagement, one form of which is ratioed tweet, as an indirect measure to gauge stakeholders' negative mood toward the firm, lending support for ratioed tweet as a proxy for perceived controversy in tweets. In line with social media's *cancel culture,* which entails the withdrawal of any public support for the company in the face of "unacceptable" actions or messages (Ng, 2020), I believe that the level of controversy in CEO tweets spark significant market reactions for the firms' stocks.

To test my prediction, I have collected S&P 500 CEO tweets sent from 2008 to 2021. However, based on the notion that a high ratio of replies to retweets is considered controversial (Troy, 2022), my sample for the main hypothesis test excludes tweets that have high retweet counts. This ensures the tweets under investigation capture "controversial" tweets – the main construct of the paper. This subsampling also reduces the concern that results may be influenced by the number of times they have been circulated or retweeted on the social media increasing investor attention (Nekrasov et al., 2021), and not due to controversy. The tweet data is then merged with event-study outcomes and firm-year-level data. My final sample contains 452 observations ranging from the year 2019 to 2021.

The main hypothesis test results reveal a significant and negative relationship between *Ratioed Tweet Score,* which represents the replies-to-retweet ratio of controversial tweets, is significantly and negatively related to cumulative abnormal returns (*CAR)*. Results thus suggest that high controversy in CEO tweets is associated with lower abnormal stock returns.

Next, I test for any cross-sectional variation in the results. The first set of cross-sectional tests involves firms with star CEOs. The logic is that celebrity CEOs can act as social media influencers, who can shape, alter, and change the attitudes and perceptions of the online community (Freberg et al., 2011). Also, celebrity CEOs can influence how firms perform (Bui et al., 2022). I leverage this idea and design a cross-sectional test to investigate if "stardom" has a differential impact on how tweet controversy influences stock price. Using search frequency data of CEOs in Google as a proxy to identify Star CEOs (Da et al., 2011; Drake et al., 2012), I show that when *Star CEOs* post messages with controversy, it intensifies the negative impact of the stock price. In a second cross-sectional test focusing on firms with low institutional (high individual) ownership, I show that shareholders' ownership moderates the relationship between CEO tweets and market returns. Namely, the tweet controversy's negative stock market effect reverses for a higher level of individual ownership. My result complements the evidence from earlier research (Barber et al., 2009; Shleifer & Summers, 1990), suggesting that investor sentiment can affect individual trades, causing prices to deviate from underlying fundamentals. The findings are broadly consistent with the view that individual investors behave as noise traders (Foucault et al., 2011); in this case, the trades result in positive market returns, although the tweets seem controversial.

Even after including fixed effects in the regression model, there could be influence from unobservable omitted variables. To reduce the endogeneity concern first, I design a two-stage least squares (2SLS) regression. To this end, I used a sample of tweets (N =1,067) that includes both ratioed tweets and non-ratioed tweets and created an indicator variable, *Ratioed*, that takes the value of 1 if the tweets receive more replies that retweets, and 0 otherwise. With that newly measured variable, I investigate potential determinants of tweets getting ratioed and find the instrument, the natural logarithm of the *Number of Twitter Followers*, to be one of the significant determinants of *Ratioed* tweets. The results of the 2SLS test support my findings that controversial CEO tweets is value-relevant and generates negative abnormal market returns. Second, I re-run the main test with an alternative sample of CEO tweets – without adjusting for the number of retweets and outliers – and found the results are similar to those with the main sample. Finally, through propensity score matching, I show that there are no statistically significant differences in the firm characteristics of the two groups, *Ratioed* and *Not Ratioed*, further reducing the sampling bias. In additional analysis, I test a subsample of retweet counts to show the variation in the impact of controversial tweets for different levels of investor attention (Nekrasov et al., 2021).

My paper primarily contributes to the capital markets research that explores how social media can influence the stock market (Bartov et al., 2018; Blankespoor et al., 2014; Tang, 2018). The distinct contribution of my paper is that not only do the tweets sent by CEOs matter (Crowley et al., 2021; Elliott et al., 2018), but also, when the Twitterverse finds CEO messages are controversial, the stock market reacts negatively. Future studies can broaden research on controversial tweets by studying, for example, the significance of tone and content of controversial tweets and whether there is any real impact of controversial CEO messages on firms' sales, customer satisfaction, goodwill, etc. Controversial tweets can be further examined as a determining factor of CEO hire/fire decision and their compensation.

I have organized the rest of the paper in the following sequence: section two includes theory and core hypothesis, section three covers research design and data, section four highlights analysis of findings, and section five discusses the results and concludes.

2. Theory and Hypothesis

CEOs act as social media influencers who can shape, alter, and change the attitudes and perceptions of an online community (Freberg et al., 2011). Especially after April 2013, when the SEC permitted CEOs to disclose information on their personal Twitter handles, communication on Twitter surged so much that CEOs like Elon Musk (CEO of Tesla Motors) alone can influence the stock market through their tweets.[2]

There is an established field of research on public engagement with organizational leaders on digital platforms (Cho et al., 2014; Gómez-Carrasco et al., 2021; Ji et al., 2019; Saxton & Waters, 2014). Amongst the mediums of user engagement, research shows that the number of followers, likes, and retweets convey significant meaning (Dobija et al., 2023; Ji et al., 2019; Nekrasov et al., 2021; Saxton & Waters, 2014). A less-explored form of response in academic research is when a tweet receives more replies than retweets and likes, commonly known as a ratioed tweet, indicating that users have found the tweet questionable and controversial (Harris, et al. 2023; Rezaee et al., 2022; Troy, 2022). In the political context, Minot et al. (2021) investigated retweet-to-reply ratios. They found evidence suggesting that Donald Trump's tweets have more replies than retweets compared to Obama's and that Trump's tweets are thus more often controversial. Also, Rezaee et al. (2022), using likes-to-replies ratio and analyzing both field and experimental data, documented that the more likes a tweet receives, the more it is perceived as credible.

Evidence shows that tweets generate cumulative abnormal returns and that they can influence bid-ask price and trading volume (Bartov et al., 2018; Blankespoor et al., 2014), suggesting tweets fill an existing information asymmetry in the stock market. Literature also shows Twitter users rely more on a piece of information when it is posted from a CEO's personal Twitter handle than when it is communicated through other information channels of firms due to the social bond with and the trust of the CEOs (Elliott et al., 2018). This indicates that there will

[2] In 2022, Business Insider reports how Elon Musk moves markets with a single tweet. https://twitter.com/i/events/1532819332794830848

be a stock market reaction when Twitterverse finds CEO tweets objectionable and controversial. Besides, online "firestorms," negative word-of-mouth dynamics on social media as well as the "cancel culture" can alter the signal the CEOs originally intend to send to the market via their tweets (Ng, 2020; Pfeffer et al., 2014) – ultimately getting them ratioed by the Twitterverse. Building on the above logic, I expect that tweets that Twitter users consider controversial negatively impact firms' stock returns. Formally, I state my hypothesis as follows:

Hypothesis: For controversial CEO tweets, the greater the level of controversy, the lower the abnormal stock returns.

3. Research Design and Data

I test the relationship between controversy and cumulative abnormal returns (*CAR*) with the following equation:

$$CAR_{it} = \beta_0 + \beta_1 Ratioed\ Tweet\ Score_{ijt} + Firm\ controls_{it} + Industry\ FE + Year\ FE + \varepsilon_{it} \quad (1)$$

In the above equation, CAR_{it} is the cumulative market-adjusted abnormal returns over the two days starting from the day (t_0) CEOs posted highly ratioed tweets. The independent variable $\beta_1 Ratioed\ Tweet\ Score_{ijt}$ is a ratio of replies to retweets for CEO j of firm i during event date t_0. To control for the potential impact of extraneous, confounding, and omitted factors, the regression equation includes firm controls that may influence abnormal stock returns. Precisely, I control for *Firm Size*, *Book-to-Market*, and *Leverage* to control for firm characteristics and valuation. I also control for *Returns Trend*, measured by the cumulative abnormal market-adjusted returns over the past 20 days. The variable definitions are included in Appendix A. I include industry and year-fixed effects to control for potential heterogeneity across industries and time. The standard errors are robust and clustered at the firm level.

To collect data for *Ratioed Tweet Score*, I first accessed the Twitter API using custom Python code to download all tweets (along with associated counts of retweets, likes, and replies) sent by S&P 500 CEO Twitter handles from 2008-2021 that I had hand collected in 2020.[3] I selected tweets with higher replies and lower retweet counts to ensure my data reflects highly controversial tweets. I then generated the measure *Ratioed Tweet Score* by dividing replies by retweets. After keeping the controversial tweets, running event studies over the controversial

[3] I have all tweets sent by the CEOs from 2020 but depending on how many tweets a CEO had sent; I could get all the tweets back to 2008 because the API allowed me to get the latest 3,200 tweets per CEO.

tweet window t_0 and t_1, and excluding the missing observations and outliers,[4] my final sample results in 452 observations ranging from 2019 to 2021. The details of the sample selection are presented in Table 1.

[INSERT TABLE 1 HERE]

4. Analysis of Findings

4.1 Descriptive Statistics

As anecdotal evidence, in Figure 1, I provide examples of sample tweets sent by two renowned CEOs. Evidence shows how audience responses, in the forms of likes, replies, and retweets, vary between tweets of the same CEO. For instance, while one tweet by Elon Musk on May 30 is not ratioed (more retweets than replies), another tweet on June 16 is ratioed (more replies than retweets). This indicates that tweets being ratioed may not be dependent on the Twitter handles but rather on the controversial message they contain.

[INSERT FIGURE 1 HERE]

In Table 2 Panel A, I include the descriptive statistics for the main regression variables. The variable *CAR* around the CEO tweets in my sample is not absolute. Recalling that my sample of 452 tweets contains controversy level to a greater or lesser extent, the CAR's min-max values indicate that the tweets may have messages considered both "good" and "bad" by Twitter users, with a mean value of -.0009. The main independent variable, *Ratioed Tweet Score*, which is the ratio of replies to retweets, has a mean value of 4.6. The mean value of ratios indicates that, on average, there are around five replies for every retweet. Amongst the firm-specific controls, the average *Firm Size* stands at 11.0650, and the *Book-to-Market* ratio shows a mean of 0.0003. Leverage has a mean of -0.5111 with a substantial SD of 6.48. Lastly, the Returns Trend exhibits an average of 0.0072; with an SD of 0.0771 that denotes a moderate return fluctuation over 20 days preceding the controversial tweet events. In Panel B, I show the descriptive statistics of the variables in the regression model by year. My sample represents three years of data – 2019, 2020, and 2021. Results indicate most of the observations are from year 2021 and that the average *Ratioed Tweet Score* is much higher in 2021 than previous two years. These

[4] Preliminary descriptive statistics, including boxplots and scattergram indicate the existence of outliers. Further inspection reveals that the outlier tweets were sent by the CEO of Activision Blizzard, Robert A. Kotick. To reduce the bias resulting from outliers, I deleted all 14 tweets sent by Robert A. Kotick. In robustness nest, I further added back the outliers along with tweets with low retweet counts and find result similar to that of the baseline regression.

outcomes suggest a growing trend of controversy in CEO tweets over the years. There is no notable variation in other variables. In Panel C, I assess the correlation matrix for the variables of the main regression equation. The findings reveal *CAR* is significantly correlated with all other variables. So is *Firm Size*. However, none of the variables are subject to multicollinearity concern as the coefficients are low. Besides, in untabulated results, I find no indication of multicollinearity as none of the VIFs are above 2.

[INSERT TABLE 2 HERE]

4.2 Ratioed Tweet Score and Market Returns

The main hypothesis test result is in Table 3. The findings reveal that the relationship between *Ratioed Tweet Score* and *CAR* is negative and significant ($\beta_1 = -0.0002^{**}$), which indicates that the higher the controversy level, the lower the abnormal stock returns. The effect is such that stock market returns reduce by .02% for a hundred percent change in the tweet ratio. For instance, if the controversy level in a CEO tweet increases from 1 (one reply for a retweet) to 2 (two replies for a retweet), the stock market return decreases by a .02%. Not all of the firm controls are statistically significant. While *Firm Size* and *Leverage* are insignificant, growing firms negatively impact cumulative abnormal returns, as indicated by the significant negative coefficient of *BTM* ($\beta = -14.1$). *Returns Trend* is also statistically significant and positive ($\beta = 0.05$) regarding its relationship with *CAR* generated during the tweet events.

[INSERT TABLE 3 HERE]

4.3 Cross-Sectional Analysis

4.3.1 Star CEOs and Ratioed Tweet Score Effect

On social media, celebrity CEOs act as social media “influencers” who can shape, alter, and change the attitudes and perceptions of an online community (Freberg et al., 2011). Besides, the leadership of CEOs is reflected in firm performance (Bui et al., 2022). Based on this notion, I expect that the stardom of celebrity CEOs will likely have an intensifying effect on the relationship between the level of controversy in their tweets and its impact on the price of their companies’ stock. Previous research has measured the “stardom” of CEOs by using search frequency in Google as a proxy (Koh, 2011; Malmendier & Tate, 2009). Search frequency of CEOs in Google as a proxy for CEO stardom aligns with public attention and investor attention arguments, which explains how retail investors demand information and search for information online (Da et al., 2011; Drake et al., 2012). Following Sabherwal and Uddin (2019), I downloaded my sample's yearly search volume index (SVI) for each CEO year. I sorted the scores into quintiles based on the average SVI. I then measured *Star CEO* as a categorical variable, which is equal to 1 for CEOs in the highest quintile and 0 otherwise. The results of the cross-sectional variation (Table 4) show that with an interaction variable, *Star CEO,* in the equation, both the main effect of *Ratioed Tweet Score* on *CAR* and the interaction effect of *Star CEO* and *Ratioed Tweet Score* on *CAR* are negative and significant. Although significant at the 10% level, the negative effect of controversy when the CEOs are stars is slightly higher. This suggests that the stardom of CEOs intensifies the negative impact of controversial messages they post on social media.

[INSERT TABLE 4 HERE]

4.3.2 Ownership and Ratioed Tweet Score Effect

In another cross-sectional test, I test whether the impact of controversy in tweets intensifies for firms with more individual investors. Previous literature shows that social media has stock market consequences because of its user base, primarily uninformed individual investors (Bartov et al., 2018; Miller & Skinner, 2015). Thus, I expect to see a differential effect on price for firms with the least institutional holdings. I followed the similar approach I used for the first cross-sectional test. I sorted the scores into quintiles based on the percentage of institutional shareholdings in firms. I then measured *High Individual Ownership* as a categorical variable, which is equal to 1 for firms that are in the lowest quintile and 0 otherwise. I then tested the interaction effect between the *Ratioed Tweet Score* and *High Individual Ownership.* Test results in Table 5 show that the interaction between *Ratioed Tweet Score* and *High Individual Ownership* is positive and significant ($\beta = 0.0006^{*}$). In contrast, the main effect of the *Ratioed Tweet Score* ($\beta = -0.0007^{**}$) stays negative. Results show that the negative impact of controversy in CEO tweets reverses for firms with high individual ownership. My findings corroborate earlier research (Barber et al., 2009; Shleifer & Summers, 1990) that suggests individual trades can be affected by investor sentiment, resulting in noise trades (Foucault et al., 2011), thereby causing prices to deviate from underlying fundamentals.

[INSERT TABLE 5 HERE]

4.4 Robustness Tests

The association between controversy level in the CEO tweets and stock market returns may be confounded by two endogeneity concerns – reverse causality, that changes in stock prices may encourage CEOs to send tweets that will likely spark social media to react and other unobservable correlated variables that are omitted. My regression results include previous return trends to reduce the reverse causality bias. To further strengthen the causality argument, I design three robustness tests.

First, I employ an instrumental variable approach, which can mitigate both correlated omitted variable and reverse causality issues (Larcker & Rusticus, 2010). I use the *Number of Twitter Followers* as an instrument and design a two-stage least squares (2SLS) regression. Previous literature shows that the number of Twitter followers is associated with how influential a Twitter account is (Bakshy et al., 2011). Extending this reasoning, it can be assumed that CEOs with more followers on Twitter will have more recipients of the tweets they send. Given that the Twitterverse reacts to controversial tweets by replying (Troy, 2022) more than retweeting or liking, the higher number of followers directly influences the number of replies a tweet receives. To test if the number of followers is a significant determinant of ratioed tweets and hence qualifies as an instrument for the 2SLS test, I use the subsample of data (N= 1,067) that includes both *Ratioed* tweets (N = 452) and *Not Ratioed* tweets (N =615). In an untabulated result, I find that amongst the determinants of CEO tweets getting ratioed by the Twitterverse – *Age*, *Compensation*, *Star status*, and the natural logarithm of *Number of Twitter Follower*s – *Number of Twitter Follower*s is positively and significantly related to the indicator variable *Ratioed*. I find results with similar inferences when I replace the independent variable with *Ratioed Tweet Score*. Thus, the instrument meets the relevance criteria of 2SLS regression. Finally, intuitively, the *Number of Twitter Followers* does not directly impact stock price movement; it is only relevant when CEOs send tweets, and therefore, the instrument meets the exclusion criteria. Table 6 shows the regression result, which shows that the instrumented variable *Ratioed* is negatively and significantly related to *CAR*, suggesting that controversial CEO tweets are associated with lower stock market returns. This complements my main findings.

[INSERT TABLE 6 HERE]

Second, I designed a propensity-matched sample analysis with the same sample (N =

1067) to reduce the potential endogeneity bias in my research design. The treatment group (N =452) may not represent random selection, creating potential selection bias. To address this issue, in line with Rosenbaum and Rubin (1983) I use propensity score matching (PSM) to form tweet-year matched pairs that are most similar along the set of control variables in the main regression model. After propensity score matching, any considerable variation in *CAR* can be better attributed to CEOs posting controversial tweets rather than any imbalances in the group characteristics. The results of the matching analysis are in Table 7. Results in Panel A show that the treatment effect under the nearest neighbor matching technique is significant, which complements the paper's main findings. Panel B of Table 7 shows the results of the mean differences in the complete set of control variables in the matched sample. The results thereby reduce the concern that the results are influenced by differences in firm characteristics.

[INSERT TABLE 7 HERE]

One might argue there is self-selection bias in my sample. As the sample of controversial tweets (N= 452) is selected for investigation after excluding high retweet counts and outliers and keeping only ratioed tweets to capture “high controversy,” there is a likelihood that the sampling may influence the regression results. Therefore, as a third robustness check, I test the effect of the tweet controversy with an alternative sample of S&P 500 CEO tweets (N = 29,880) before subtracting high retweets and outliers. I re-run the event studies and the baseline regression model, the results of which are in Table 8. Results show the *Ratioed Tweet Score* has the same sign, although it is significant at the 10% level. The result reduces the concern of sampling and self-selection bias.

[INSERT TABLE 8 HERE]

4.5 Additional Analysis

In an additional analysis, I look into high-attention controversial tweets. Previous literature shows that the higher the number of retweets, the greater the investor's attention (Nekrasov et al., 2021). I intend to show what happens when the tweets CEOs send are controversial and highly visible to Twitter users due to the number of times they circulate on social media. I take subsample of tweets based on the lowest and the highest quartiles of retweet counts. I then re-run my baseline regression model. Results are in Table 9, which shows the effect of controversy in CEO tweets on CAR for the lowest quartile of retweet counts is still negative. For the highest retweet counts, the coefficient associated with the *Ratioed Tweet Score* is not significant. The result confirms that controversy in CEO tweets generate negative returns in general. One likely explanation could be, ratio of replies-to-retweet counts is lower for high retweet counts, and hence, by definition, the controversy is low for the highest retweet subsample.

[INSERT TABLE 9 HERE]

5. Discussion and Conclusion

It is well established that tweets by firms, CEOs, and third parties can influence stock prices; the notion of controversial tweets is less explored. Troy (2022) explains that when a tweet gets more replies than likes or retweets, the tweets are called *ratioed* tweets, and tweets get ratioed when Twitterverse finds a tweet objectionable and controversial. My paper takes up this idea and measures tweet controversy by the ratio of replies to retweets. The paper explores a small subset of CEO tweets that are ratioed – tweets that have more replies than retweets – and tests the relationship between the level of controversy in those tweets and abnormal stock market returns. A significant negative relationship between the level of controversy in CEO tweets and market returns indicates that Twitter is not only a valuable source of information that CEOs use to disclose the news to the public but also that the level of controversy in CEO tweets – as determined by the public's response to those tweets – is associated with the price behavior of stocks. Results show that controversy lowers abnormal market returns. The findings can be explained by social media's *cancel culture*, which is the withdrawal of support from the users due to the posts being deemed "unacceptable" or highly problematic (Ng, 2020).

To explore whether CEO and firm characteristics intensify the effect of controversy, I conducted two analyses – one with CEO stars and the other with stock ownership. I show Star CEOs' negatively influence stock prices when tweets are considered controversial. This implies CEOs on social media can shape how investors behave (Freberg et al., 2011). I also show the main effect of tweet controversy is reversed for high individual ownership. The result complements the idea that retail investors may alter expected price behavior through noise trading (Barber et al., 2009; Shleifer & Summers, 1990). Additionally, my paper shows that when retweet counts are low, and tweets are controversial, market reacts negatively. For high-attention controversial tweets, I find no significant stock market effect.

My research prompts future research questions into the area of controversial tweets, specifically, the content analysis of the tweets that may trigger conversation by Twitter users, which in turn makes the tweets ratioed. Another future study relevant to my paper could be investigating the consequences of controversial tweets for CEOs, namely CEO compensation and turnover. The influence of controversial tweets on actual business outcomes, for instance, sales, customer satisfaction, goodwill, or reputational capital, can also be explored.

My paper has practical implications for firms. As controversy in CEO tweets may harm firms' stocks, CEOs may consider posting strategically on social platforms. While investors are the major parties susceptible to controversial tweets, regulatory authorities are often interested in executives who can move markets in minutes with their messages on social media platforms.

Appendix A: Variable Definition

Variable Name	Description
Dependent Variable	
CAR	Cumulative abnormal returns [t0, t+1], with expected returns based on a market-adjusted model calculated over the [-100, 0] pre-tweet event days
Controversy Variables	
Ratioed	Coded as 1 if replies is greater than retweets
Ratioed Tweet Score	Replies-to-retweet ratio of ratioed tweets
CEO Characteristics	
Star CEO	Coded as 1 for CEOs in the highest quintile of the average score of Google's search volume index
High Individual Ownership	Coded as 1for firms in the lowest quintile of the percentage of institutional ownership
Control Variables	
Firm Size	Natural logarithm of total assets
Book-to-Market	The ratio of book to market value
Leverage	The ratio of total debt to total equity
Returns Trend	Cumulative abnormal returns for stocks for the previous 20 days of tweet events

Figure 1: Sample Tweets

Table 1: Data and Sample Selection

	No. of Observations
S&P500 CEO Tweets (62 CEOs; 62 firms)	43,674
Less: Retweet count of 0	(13,486)
High Retweet counts (> 1st quartile)	(20,482)
Outliers	(14)
Missing CARs and firm level controls	(8,625)
Not ratioed tweets	(615)
Final sample (43 CEOs, 43 firms)	452

Table 2: Descriptive Statistics

Panel A: Variables to test main hypothesis

	N	Mean	SD	Min	Max
CAR	452	-0.0009	0.0244	-0.0929	0.1910
Ratioed Tweet Score	452	4.6637	8.6441	1.3333	153
Firm Size	452	11.0650	1.1974	8.3051	12.8120
Book-to-Market	452	0.0003	0.0006	-0.0003	0.0061
Leverage	452	-0.5112	6.4818	-48.3083	6.4857
Returns Trend	452	0.0072	0.0771	-0.2061	0.2785

Table presents descriptive statistics for 452 firm-year observations. It includes mean, median, standard deviation, minimum, and maximum values of the dependent variable, *CAR*; the independent variable, *Ratioed Tweet Score* (variable showing the ratio of tweet replies to retweets); and other control variables defined in Appendix A.

Table 2: Descriptive Statistics

Panel B: Descriptive statistics by Year

Year	Variables	N	Mean	SD
2019	CAR	3	0.0018	0.1173
	Ratioed Tweet Score	3	5.1111	3.0061
	Firm Size	3	9.58628	0.1182
	Book-to-Market	3	0.0005	0.0001
	Leverage	3	.9056	.4571
	Returns Trend	3	.0231	.0662
2020	CAR	112	.0004	.0243
	Ratioed Tweet Score	112	4.6607	5.2541
	Firm Size	112	11.0055	1.1964
	Book-to-Market	112	0.0002	-.0001
	Leverage	112	-.3615	6.6688
	Returns Trend	112	.0327	.0912
2021	CAR	337	-.0014	0.0245
	Ratioed Tweet Score	337	4.6607	9.5457
	Firm Size	337	11.0979	1.1958
	Book-to-Market	337	0.0002	0.0005
	Leverage	337	-.5734	6.4553
	Returns Trend	337	-.0013	.0700

Table presents descriptive statistics for 452 firm-year observations by years. It includes mean, median, and standard deviation. *CAR*; the independent variable, *Ratioed Tweet Score* (variable showing the ratio of tweet replies to retweets); and other control variables defined in Appendix A.

Table 2: Descriptive Statistics

Panel C: Correlation Matrix

	CAR	Ratioed Tweet Score	Firm Size	Book-to-Market	Leverage	Returns Trend
CAR	1					
Ratioed Tweet Score	-0.0893	1				
Firm Size	-0.1559*	-0.0487	1			
Book-to-Market	-0.1122*	0.0226	-0.1249*	1		
Leverage	-0.1713*	0.0357	0.2819*	0.1626*	1	
Returns Trend	0.2131*	-0.0472	-0.1888*	0.0370	-0.0303	1

Panel C reports pairwise correlation coefficients between all variables used in the hypothesis tests. All variable definitions are included in Appendix A.

Table 3: Ratioed Tweet Score and Market Returns

	CAR
Ratioed Tweet Score	-0.0002** (0.0009)
Firm Size	-0.001 (0.001)
Book-to-Market	-14.1** (2.6)
Leverage	0.0001 (0.0003)
Returns Trend	0.05** (0.18)
Year and Industry Fixed Effects	Yes
Constant	0.006 (0.008)
Observations	452
Adjusted R^2	0.178

Table presents results from regression of equation (1), where the dependent variable *CAR* is the cumulative abnormal returns for S&P500 firms during the controversial tweet event windows [0 +1]. Control variables are as defined in Appendix A. Standard errors are clustered at the firm level and are shown in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 4: Cross-Sectional Analysis – Star CEOs and Ratioed Tweet Score Effect

	CAR
Ratioed Tweet Score	-0.0001** (0.00007)
Star CEO	0.012+ (0.006)
Ratioed Tweet Score × Star CEO	-0.0005+ (0.0002)
Firm Size	-0.0014 (0.001)
Book-to-Market	-14.2** (2.6)
Leverage	0.0001 (0.0003)
Returns Trend	0.05* (0.01)
Year and Industry Fixed Effects	Yes
Constant	0.009 (0.008)
Observations	452
Adjusted R^2	0.185

Table presents results from regression of a modified equation (1) with an added interaction variable, *Star CEO*, where the dependent variable *CAR* is the cumulative abnormal returns for S&P500 firms during the controversial tweet event windows [0 +1]. Control variables are as defined in Appendix A. Standard errors are clustered at the firm level and are shown in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 5: Cross-Sectional Analysis – Ownership and Ratioed Tweet Score Effect

	CAR
Ratioed Tweet Score	-0.0007 **
	(0.0002)
High Individual Ownership	0.0001
	(0.006)
Ratioed Tweet Score × High Individual Ownership	0.0006**
	(0.0002)
Firm Size	-0.0012
	(0.0009)
Book-to-Market	-14.19**
	(2.7)
Leverage	0.0001
	(0.0003)
Returns Trend	0.05**
	(0.02)
Year and Industry Fixed Effects	Yes
Constant	0.008
	(0.01)
Observations	452
Adjusted R^2	0.185

Table presents results from regression of a modified equation (1) with an added interaction variable, *High Individual Ownership*, where the dependent variable *CAR* is the cumulative abnormal returns for S&P500 firms during the controversial tweet event windows [0 +1]. Control variables are as defined in Appendix A. Standard errors are clustered at the firm level and are shown in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 6: Ratioed Tweet Score and Market Returns (2SLS)

	CAR
Ratioed	-0.003*
	(0.0014)
Firm Size	-0.001
	(0.0026)
Book-to-Market	-6.2**
	(1.2)
Leverage	.00007
	(.00008)
Returns Trend	0.034*
	(0.02)
Year and Industry Fixed Effects	Yes
Constant	-0.00009
	(0.027)
Observations	1,067

Table presents results from 2SLS regression, where *Number of Twitter Followers* is the instrument, and the dependent variable in the second-stage regression model is the cumulative abnormal returns for S&P500 firms during the controversial tweet event windows [0 +1]. Control variables are as defined in Appendix A. Standard errors are clustered at the firm level and are shown in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 7: Propensity Score Matching

Panel A: Treatment Effect (treatment = Ratioed Tweets, control = Not-ratioed Tweets)

	CAR
Ratioed	-0.00128**

Panel B: Covariate Descriptive Statistics and Tests of Differences in matched sample

	Treatment Mean	Control Mean	%bias	t-test	P > |t|
Firm Size	10.898	10.896	0.2	0.03	0.975
Book-to-Market	00031	.00031	0.01	0.02	0.983
Leverage	-.50646	-.65902	2	0.36	0.719
Returns Trend	.00625	00614	0.2	0.03	0.975

Table presents propensity-scored matched sample analysis, where the treatment group constitutes CEO tweets that are ratioed (N=452) and the control group contains CEO tweets that are not-ratioed (N=615). Panel A shows the average treatment effect *Ratioed* on the treated for nearest neighbor matching technique. Panel B shows the mean differences amongst the control variables in equation (1) for a matched sample based on the nearest neighbor matching. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 8: Ratioed Tweet Score and Market Returns (Alternative Sample)

	CAR
Ratioed Tweet Score	-0.0001^{+}
	(0.00008)
Firm Size	-0.0002
	(0.0005)
Book-to-Market	-0.8
	(0.5)
Leverage	-0.0002^{*}
	(0.00008)
Returns Trend	0.05^{**}
	(0.004)
Year and Industry Fixed Effects	Yes
Constant	0.007
	(0.009)
Observations	29880
Adjusted R^2	0.024

Table presents results from regression of equation (1), where the dependent variable *CAR* is the cumulative abnormal returns for S&P500 firms during the controversial tweet event windows [0 +1]. Control variables are as defined in Appendix A. Standard errors are clustered at the firm level and are shown in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 9: Subsample Tests of Ratioed Tweet and Market Returns

	$CAR_{[0, +1]}$	
	Sub-Sample Based on High-Attention Tweets	
	1st Quartile of Retweet	4th Quartile of Retweet
Ratioed Tweet Score	-0.0006^{*} (0.0002)	0.0001 (.0008)
Firm Size	-0.004^{*} (0.002)	0.004 (.002)
Book-to-Market	-15.0^{**} (2.8)	8.1 (13.3)
Leverage	-0.0002 (.0004)	0.0007^{*} (.0002)
Returns Trend	0.03 (0.03)	.03 (.05)
Year and Industry Fixed Effects	Yes	Yes
Constant	-0.05 (0.04)	-0.04^{+} (.02)
Observations	217	107
Adjusted R^2	.109	-0.007

Table presents results for the lowest and the highest quartiles of retweet counts. The dependent variable *CAR* is the cumulative abnormal returns for S&P500 firms during the controversial tweet event windows [0 +1]. Control variables are as defined in Appendix A. Standard errors are clustered at the firm level and are shown in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Chapter Three: The Market Effects of Controversial Firm Tweets and the Moderating Role of Sentiment

1. Introduction

In today's dynamic digital landscape, social media has evolved into a platform where conversation has become more casual. Whether it is the likes, retweets, replies, or even growing follower counts, each interaction on a platform such as Twitter wields the potential for posts to go viral instantly. When Tesla's CEO, Elon Musk, tweets about company developments, the response is not confined to casual commentary. His tweets have been known to trigger notable fluctuations in Tesla's stock price, underlining the substantial impact of social media on the stock market. This real-world example vividly illustrates tweets' influence on market dynamics. Previous studies have revealed this connection between Twitter activity and the stock market (Arteaga-Garavito et al., 2020; Bartov et al., 2018; Blankespoor et al., 2014; Lee et al., 2015; Tang, 2018), yet what truly captures my attention is the notion of tweets being "ratioed." This occurs when a tweet receives more replies than retweets or likes in case the Twitterverse finds the tweet's message problematic and objectionable (Troy, 2022). My initial curiosity about this phenomenon leads me to two pivotal research questions that form the core of my study. My first research question is, "Do controversial firm tweets influence long-run abnormal market returns?" Unlike the previous chapter, which looked at controversial CEO tweets, in this chapter I look at tweets sent by the firms' Twitter accounts. Moreover, in contrast to daily tweets, I hypothesize that an aggregate and prolonged controversy stemming from a firm's social media communications across an extended period may yield a more substantial and lasting impact on the stock performance. Therefore, I posit that when firms have a higher level of controversy – where annual average replies surpass annual average retweets– there will be a significant change in long-run abnormal stock market returns for those firms. Secondly, complementary to the recent studies that argue tweet sentiment is influential in determining market returns (Gu & Kurov, 2020; Sampath et al., 2022), I pose a second research question: "Does tweet sentiment intensify the effect of controversial tweets on long-run abnormal market returns?" Finally, in line with the notion that earnings announcement events are one of the most significant events that influence stock prices (Barber & Lyon, 1997; Bernard & Thomas, 1989; Pan & Poteshman, 2006) and that Twitter activity is reportedly higher during these events (Da et al., 2011), in additional analysis I explore whether long-term tweet controversy intensifies the market reaction to earning news.

To answer my research questions, I accessed the Twitter application programming interface (API) using custom Python code to download all tweets (along with associated counts of retweets, likes, and replies) sent by S&P 500 Twitter handles from 2020 to 2021 that I had hand collected in 2020.[5] From an extensive dataset comprising millions of tweets, I then measure the annual average reply-to-retweet ratio for each of the S&P500 firms from 2020 to 2021 to measure the independent variable for the hypotheses tests with *Ratioed Tweet*, which takes the value of 1 if a firm-year level reply-to-retweet ratio is greater than 1; otherwise, 0. Upon integrating the dependent variable, *Abnormal Returns*, which is the long-run abnormal returns for stocks for 2020 and 2021, and the control variables for 2019 and 2020, the final sample to test the main hypotheses constitutes 514 observations. Moreover, for additional analysis, I gather quarterly earnings announcement data for S&P500 firms between 2020 and 2022 from I/B/E/S to determine the intensifying effect of tweet controversy on the stock market reactions to earnings news.

Results indicate that controversial firm tweets are associated with positive significant long-run abnormal stock market returns. The findings complement the notion that more engagement and popularity amongst the public can be positive regardless of what sparks that engagement (Minot et al., 2021). The findings can also be explained by the price distortion behavior of the social media (Jia et al., 2020). Intuitively, the "cancel culture" prevalent on social media (Ng, 2020) would harm firms when they post problematic social media messages. The result is interesting as it portrays how the relationship between controversial firm messages and long-run abnormal stock market returns can be positive. An in-depth sentiment analysis of the firm-generated tweets reveals that while the main effect of controversial tweet is insignificant, the impact on stock returns is favorable with more positive tweet sentiment. This implies that when controversial tweets convey a positive tone, they potentially yield a beneficial outcome for investors.

To comprehend the rather unexpected results I found in the main test – how firm tweets perceived as controversial by the Twitterverse are associated with positive abnormal returns – I

[5] My sample contains tweets between 2020 and 2021 but depending on how many tweets a firm had sent; I could get all the tweets back to 2010 because the API allowed me to get the latest 3,200 tweets per firm.

test the relationship between highly ratioed tweets and long-run abnormal market returns for each quartile of retweets. The rationale behind the design is that a highly-ratioed (and hence controversial) firm tweet garners more replies than retweets. Since retweets indicate investor attention on social media platforms (Nekrasov et al., 2021), the absence of substantial retweet activity on a controversial tweet might lead to information gap. The test's findings substantiate this presumption, revealing that when controversial tweets are less retweeted, they are linked with positive stock market returns. Overall, the findings imply that it is not solely the controversial nature of tweets posted by firms that establish the relationship between firm tweet response and stock market performance but also the extent of dissemination of the message. Finally, another additional analysis suggests that the effect of average tweet controversy is substantial around one of the most significant events for a firm – earnings announcement events. The results indicate that the controversy level of tweets reduces the positive stock market reaction to good news.

My paper primarily contributes to capital markets research exploring how social media responses influence firms' stock pricing. My paper is the first, so far as I am aware, that explores the relationship between controversial firm tweets and long-run abnormal stock market returns. Besides, research findings about the capital market relevance of tweet sentiment have been mixed so far. While some research suggests the sentiment in tweets influences stock price movements (Debreceny et al., 2021; Karampatsas et al., 2023), others argue there is no significant association between tweet content and stock price or Twitter sentiment signals are only considered reliable when the sentiment persists over a long enough period (Behrendt & Schmidt, 2018). My study complements previous research that argues tweet sentiment is value-relevant such that positively oriented tweets, even when controversial, are positively related to stock returns in the long run. Finally, my paper contributes to the earnings announcement literature by showing how controversy in social messages around a significant event can regulate how stock prices move. The practical implication can be gauged from understanding how firm messages on social media can be formed to influence financial outcomes strategically. Future studies can be designed to examine any substantive impact of controversial tweets on firms' economic outcomes such as sales, customer satisfaction, goodwill, etc.

The rest of the paper is organized as follows: section two includes a brief institutional background, section three describes the theory and hypotheses, section four covers research design and data, section five highlights analysis of findings, and section six discusses the results and concludes.

2. Institutional Background

On April 2nd, 2013, the Securities and Exchange Commission (SEC) issued a statement allowing firms and executives to report firm-specific information on their social media accounts, given that the information disclosed is public. However, social media communication constitutes not merely one-way communication but also two-way dialogue whereby users can communicate their responses to firm tweets in various ways, including retweets, likes, mentions, and replies (Minot et al., 2021; Saxton et al., 2021). A *ratioed* tweet, a social media post that gets more replies than likes or retweets, is one such collective user response (Troy, 2022). A Data for Progress report (*The Ratio Richter Scale, 2023*) explains the underlying logic in how replies are more likely to reflect objections from Twitter users. The logic is that it takes a lot more effort to find, read, and reply to a tweet than to just like or retweet it while scrolling through the feed and that Twitter users are more likely to make an effort when finding the tweet objectionable.[6] Table 1 highlights tweets that, although seemingly harmless, received a substantial number of unfavorable reactions from the Twitterverse, implying that they might have been perceived as objectionable.

[INSERT TABLE 1 HERE]

3. Theory and Hypothesis

There is a well-established body of literature on Twitter's impact on the capital markets. Blankespoor et al. (2014) was one of the pioneering studies that showed that information asymmetry is reduced when firms provide press release links in their Twitter feeds. Also, it has been found that adverse price reactions for firms that recall products can be reduced by firms' tweets (Lee et al., 2015). Research also shows that third-party generated tweets about products and brands can predict firm sales (Tang, 2018) and that aggregated individual tweets can

[6] In a New York Times article Mike Isaac writes, "Divide the number of replies you get to a tweet by the number of likes and retweets. If the former category is much larger than the latter, you probably tweeted something awful" https://www.nytimes.com/interactive/2018/02/09/technology/the-ratio-trends-on-twitter.html

successfully predict a firm's upcoming quarterly earnings and returns (Bartov et al., 2018), more prominently when the level of advertisement is low or when a firm's information environment is weak. These studies establish the claim that information posted on Twitter is value-relevant, either because it disseminates firm-specific information more broadly, reducing information asymmetry, or because of the "wisdom of crowds." There is a third set of arguments that the Twitter effect on stock price could reflect price distortion behavior, in contradiction of the efficient market hypothesis (Jia et al., 2020). In their paper, Jia et al. (2020) shows evidence that third-party tweets significantly impact cumulative abnormal returns for stocks subject to merger and acquisition rumors and that the effect is reversed in the long run, explaining how third-party Twitter activity can distort stock prices.

Controversial tweets, not yet examined in the capital markets setting, have been explored chiefly in political research. Minot et al. (2021) investigated the retweets-to-replies ratio. They found evidence that Donald Trump's tweets have more replies than retweets than Obama's and that Trump's tweets are more often seen as controversial. When firms post messages that the Twitterverse finds controversial, online firestorms that are negative word-of-mouth dynamics of social media as well as the "cancel culture" can consequently alter the signal the firms originally intend to send to the market via their tweets (Ng, 2020; Pfeffer et al., 2014). While Nekrasov et al. (2021) found evidence that likes and retweets help generate investor attention on new information embedded in firm tweets, Ng (2020) argues that Twitterverse replies more than they retweet or like tweets when they find content objectionable. Building on the above logic, I expect that the firm tweets that the Twitterverse finds controversial – as indicated by the average replies to retweet ratio over the year– will significantly impact the firm's long-run stock returns.

Ex ante, it is not clear whether the rationing of firm tweets by Twitterverse will have a positive or negative impact on the stocks. While social media's *cancel culture* dictates a negative consequence for the firms' stocks when firms post controversial messages (Ng, 2020), any form of engagement, be it positive or negative, may generate positive reactions in the stock market (Minot et al., 2021). There is the likelihood of price distortion behavior as well. Therefore, I state my first alternate hypothesis in a non-directional form:

H_1: Long-run abnormal stock market returns are significantly affected by controversial firm tweets.

The findings on the impact of tweet content have been mixed. Drawing upon investor attention and moral leadership theories, Sampath et al. (2022) use linguistic textual analysis and examine the degree to which tweet sentiment explains variations in market returns. The authors argue that sentiment associated with authenticity and self-praise are positively associated with stock market returns. However, emotional tone, insight, risk, and credibility deficit are negatively associated with market returns. A similar finding is reported by Gu and Kurov (2020), who argue that Twitter sentiment provides new information about analyst recommendations, analyst price targets, and quarterly earnings. However, some studies do not find a significant, differential impact of tweet sentiment on company stocks (Behrendt & Schmidt, 2018; Juma'h & Alnsour, 2018). This contradictory argument in the previous literature motivates my second hypothesis.

To examine the conditioning effect of sentiment, I operationalize two distinct dimensions of sentiment highlighted in the literature: polarity and subjectivity. The concept of tweet sentiment polarity constitutes a fundamental component within sentiment analysis, encompassing the process of classifying the sentiment expressed in a statement as positive, negative, or neutral. Pang et al. (2002) pioneered this field by investigating sentiment classification and leveraging machine learning algorithms. Later, Zhang et al. (2018) introduced an approach to classifying tweet sentiment polarity. Their investigation underscored the proficiency of deep learning models in accommodating the distinctive attributes of Twitter data, including the conciseness and informal language of tweets. While sentiment polarity focuses on sentiment valence, subjectivity analysis provides a deeper understanding of the sentiment. Wiebe et al. (2005) emphasized distinguishing between subjective and objective expressions in sentiment analysis. Furthermore, advances in subjectivity analysis, such as the Subjectivity Lexicon, provide a valuable tool for identifying emotional language in text, which can be adapted for use in Twitter sentiment analysis.

For my second hypothesis test, which includes tweet sentiment in the equation, I presume, as firm tweet sentiment influences a firm's stock behavior, it can intensify the effect of controversial tweets, such that more positively structured tweets are expected to curb any potential negative consequence of controversy in tweets, and that more objective tweets are expected to influence likewise. The hypotheses are stated in the following forms:

H2a: The polarity of controversial firm tweets intensifies long-run abnormal stock market returns.

H2b: The subjectivity of controversial firm tweets intensifies log-run abnormal stock market returns.

4. Research Design and Data

I test the first hypothesis, which examines the relationship between controversial tweets and long-run abnormal stock market returns, with the following equation:

$$Abnormal\ Returns_{it} = \beta_0 + \beta_1 Ratioed\ Tweet_{ijt} + Firm\ controls_{it} ++ Industry\ FE + \varepsilon_{it}\ (1)$$

In the above equation, *Abnormal Returns*$_{it}$ is the annual abnormal returns of firm ***i*** in year *t*. Using the notion of long-run (yearly) abnormal returns of Henderson et al. (2010) and following the measurement of long-run buy and hold abnormal returns proposed by Barber and Lyon (1997), I measure *Abnormal Returns* as the difference between annual actual returns of stock i and annual benchmark return of the S&P500 market index. The independent variable, *Ratioed Tweet*, is a dummy variable that is equal to 1 if the annual average ratio of replies to retweets for firm i in year t is greater than 1, and 0 otherwise. Firm control variables, such as *Firm Size, Book-to-Market, Return on Assets, Institutional Ownership, Media Coverage, Analyst Following* are defined in Appendix B.

I accessed the Twitter API using custom Python code to download all tweets (along with associated counts of retweets, likes, and replies) sent by S&P 500 firm Twitter handles that I hand-collected in 2020. After I merged tweet-level data with firm-year-level data, my final sample, excluding missing controls, contained 514 observations. I have collected the stock price information from CRSP, earnings announcement data from I/B/E/S, and all other firm-level variables from COMPUSTAT. The details of the sample selection are in Table 2.

[INSERT TABLE 2 HERE]

For the H2a and H2b tests, I run the following regression models:

$$Abnormal\ Returns_{it} = \beta_0 + \beta_1 Ratioed\ Tweet_{it} + \beta_2 Ratioed\ Tweet_{it} \times Polarity + Firm\ controls_{it} + Industry\ FE + \varepsilon_{it}\ (2a)$$

$$Abnormal\ Returns_{it} = \beta_0 + \beta_1 Ratioed\ Tweet_{it} + \beta_2 Ratioed\ Tweet_{it} \times Subjectivity + Firm\ controls_{it} + Industry\ FE + \varepsilon_{it}\ (2b)$$

Using custom Python code, I implement machine learning algorithms to analyze the sentiment of the S&P500 firm tweets in my sample and determine polarity and subjectivity scores for each tweet. First, in line with best practices, I remove special characters, hyperlinks, retweets, emojis, and stickers and then tokenize the tweet text. Then, I used the package TextBlob, which is a pre-trained NLP (Natural Language Processing) library to calculate the *Polarity* and *Subjectivity* scores for each tweet text. In this study, the variable *Polarity* is the average score firms receive based on the polarity score of all the tweets they have posted over a year. For the variable *Subjectivity*, I calculated the average of the subjectivity scores the program generated for all the tweets the firms posted over a year.[7] I am interested in understanding the significance and direction of the impact that the interaction between the sentiment scores and controversial tweets has on market returns.

5. Analysis of Findings

5.1 Descriptive Statistics

The sample of 514 firm-year observations is used to test both *H1* and *H2*. However, to run the additional test with quarterly earnings announcement event studies, I employ a sample of 2,497 firm-event observations. I report the descriptive statistics for both samples in Table 3.

[INSERT TABLE 3 HERE]

In panel A, I show the descriptives for the variables used to test first, the main effect of controversial tweets (*H1*), and second, the intensifying effect of tweet sentiment (*H2*), on the long-run abnormal stock returns. As noted previously, the variable *Abnormal Returns* is the long-run annual abnormal returns that the stocks earned over the return on the S&P 500 market index. *Abnormal Returns* are not absolute, and the negative mean value indicates the effect of controversial tweets can have a detrimental impact on firms' stocks. It has a mean of -0.0015, indicating a slightly negative average abnormal return, with a standard deviation (SD) of 0.0091,

[7] In untabulated results, I show there are no significant results when I measure polarity and subjectivity as indicator variables, such that *Polarity* takes the value of 1 when the average score for a firm-year is higher than 0, and 0 otherwise, and *Subjectivity* takes the value of 1 when a firm-year score is higher than the sample mean, and 0 otherwise. Further analysis shows only nine observations have negative polarity scores in my sample. The findings thus indicate that relative positivity matters for the tweets to influence stock returns.

suggesting relatively low variability around the mean. *Ratioed Tweet* shows a mean of 0.2082, indicating that my sample has more not-ratioed tweets than ratioed tweets. Other than *Media Coverage*, none of the control variables have higher dispersion. Finally, *Polarity* shows a mean of 0.1764, indicating a predominantly positive polarity in the dataset, with a relatively low SD of 0.0831. *Subjectivity* has a mean of 0.3888, suggesting a moderate level of subjectivity.

In Panel B, I assess the correlation matrix for the variables under investigation. The findings reveal *Firm Size* is statistically correlated with other control variables. However, none of the correlation coefficients are above 0.4. Untabulated results also reveal VIFs are lower than 2. This finding helps allay potential concerns related to multicollinearity in the subsequent regression analysis.

In Panel C of Table 3, I show the descriptive statistics for the additional test – the effect of tweet controversy around earnings announcement events. *CARs* around the two-day event window [0, +1] are not absolute. Recalling that my sample of 2,497 observations contain controversy of tweets that are all "ratioed" to a greater or lesser extent, the min-max values of *CAR* are indications that the tweets around earnings announcement events may contain messages that are considered both "good" and "bad" by Twitter users, with a mean value of -0.0005. The main independent variable, *Average Controversy,* has a mean value of 3.69, with the maximum ratio value of 90.5.[8] The mean value of *Ratioed Tweet* indicates that, on average, there are around three replies for every retweet. *Good News* has a mean value of 0.7201, indicating that, on average, about 72.01% of the earnings surprise is positive. *Sentiment,* which proxies the polarity score of tweets in this sample, shows a mean of 0.1952, indicating a generally positive sentiment, with an SD of 0.1503, suggesting some variability. *Returns Trend* has a positive mean value, which implies that the abnormal returns earned by investors during the preceding 20 days of the event dates were positive.

[8] First, using a box plot and histogram indicating outliers in the sample, I identify firms that have replies to retweet scores outside of the normal distribution. In untabulated results, I find that the inferences of the main regression result hold when the outlier Tickers, such as CMCSA, AIZ, EXR and ATVI, are removed from the sample. I also find that when the ratio of replies to retweets is winsorized at 1% and 99% levels, the results are robust, and the inferences remain the same.

5.2 Main Hypothesis tests

5.2.1 Controversial Firm Tweets and Abnormal Returns

The main regression results for H1 are in Table 4.

[INSERT TABLE 4 HERE]

The results show that the coefficient for *Ratioed Tweet* is statistically significant at 1% level, indicating a positive association with *Abnormal Returns* (β= 0.01). This suggests that firms with a higher proportion of controversial tweets over the year tend to experience higher long-run abnormal returns. The finding is not intuitive, as the *wisdom of crowds* argument suggests retail markets generally know better because of the collective information (Bartov et al., 2018), and thus, it is expected that objectionable or problematic tweets would generate negative abnormal returns. Moreover, social media's *cancel culture*, which is the withdrawal of any support from the users due to the posts being deemed "unacceptable" or highly problematic (Ng, 2020), is expected to lead to negative stock market returns. A significant positive association between controversial firm tweets and stock price can be somewhat explained as a price distortion behavior on social media (Jia et al., 2020). To reduce potential endogeneity bias that the result may be driven by other omitted variables, such as firm characteristics or other concurrent events occurring around the same time, I run the regressions after controlling for firm characteristics and industry fixed effects. Amongst the controls, *Size* exhibits a statistically significant negative relationship with *Abnormal Returns* (β=-0.002), indicating that larger firms tend to have lower *Abnormal Returns*. Additionally, *Return on Assets* displays a negative and statistically significant association with *Abnormal Returns* (β=-0.04). Furthermore, *Institutional Ownership* demonstrates a statistically significant negative relationship with *Abnormal Returns* (β= -0.003), indicating that firms with higher institutional ownership tend to have lower abnormal returns. Intuitively bigger firms and firms with a higher number of institutional owners are expected to have lower information asymmetry and a more efficient information environment, giving less opportunity to earn abnormal returns from trades.

5.2.2 Sentiment of Controversial Firm Tweets and Abnormal Returns

The results of the second hypotheses (*H2a and H2b*) tests are in Table 5. The results in Panel A show that when *Polarity* is in the equation, the main effect of *Ratioed Tweet* on abnormal returns loses significance. *Polarity* (β= -0.01) is negatively and significantly associated with *Abnormal Returns,* whereas the interaction term between *Ratioed Tweet* and *Polarity* is positive and statistically significant at the 5% level (β= 0.006). This indicates that although the main effect of positive sentiment in firm tweets is negatively correlated to abnormal stock market returns, in the long run, the combined effect of positive sentiment for highly ratioed firm tweets leads to positive abnormal returns. In Panel B, I report the results I find with *Subjectivity* as an interaction variable; however, I find no significant association between *Abnormal Returns* and the interaction of *Ratioed Tweet* and *Subjectivity*.

[INSERT TABLE 5 HERE]

5.3. Robustness Tests

To see whether the results hold for variations in the independent variable, I use an alternative independent variable for the first hypothesis test. I replaced the indicator variable *Ratioed Tweet* with the continuous variable *Ratioed Tweet Score*, which measures the average replies to retweets ratios for controversial firm tweets. Table 6 shows that the results have similar inferences. Results suggest that the higher the annual average replies-to-retweet ratio for a firm, the more positive the long-run abnormal stock market returns are.

[INSERT TABLE 6 HERE]

The results may be subject to endogeneity bias even after controlling for firm characteristics and including fixed effects in the main regression model. The controversial tweets may affect the stock market in nonlinear ways. Besides, the treatment group in the sample, which includes firms posting tweets that get ratioed, may not represent random selection, creating potential selection bias. To address these issues, in line with Rosenbaum and Rubin (1983), I use propensity score matching (PSM) to form firm-year matched pairs that are most similar along the set of firm characteristics included as control variables in equation (1). Recall from the main findings that there is a significant variation in long-run abnormal returns due to firms' controversial tweets. After propensity score matching, any considerable variation can be better attributed to firms posting controversial tweets rather than any imbalances in the group characteristics. The results of the matching analysis are in Table 7. Following Jha et al. (2021), I use different matching algorithms in each column because each algorithm provides different bias and treatment effects (Smith & Todd, 2005). Results in Panel A of Table 7 show that the treatment effect under each specification is significant, which complements the paper's main findings. Panel B of Table 7 shows the results of the mean differences in the complete set of control variables in the matched sample. While I am unable to obtain a full covariate balance, this robustness test suggests that the relationship I find between controversial tweets and long-run abnormal stock returns is not entirely due to the group characteristics.

[INSERT TABLE 7 HERE]

5.4. Additional Analysis

5.4.1 Market Reaction to Average Tweet Controversy Level Around Earnings Announcement Events

In line with the notion that earnings announcement events are one of the most significant events that influence the stock price (Barber & Lyon, 1997; Bernard & Thomas, 1989; Pan & Poteshman, 2006) and that Twitter activity is reportedly higher during these events (Da et al., 2011), I conjecture that firms' average level of tweet controversy would intensify the stock market reaction of earnings announcement events. To test my presumption, I run event studies around a two-day window [0,+1] of quarterly earnings announcement events of S&P500 firms between 2020 and 2022. Next, I test the effect of *Tweet Controversy*, which is tweets' lagged annual average controversy level on stock market reactions to earnings news with the following model.[9]

$$CAR_{it} = \beta_0 + \beta_1 Average\ Controversy_{it} + \beta_2 Average\ Controversy_{it} \times Good\ News_{it} + \beta_3 Average\ Controversy_{it} \times Good\ News_{it} \times Sentiment_{it} + Firm\ controls_{it} + Industry\ FE + \varepsilon_{it} \quad (3)$$

I am interested in finding whether and how *Average Controversy* intensifies the impact of *Good News* on stock market returns, where *Good News* is a categorical variable that takes the value of 1 when actual earnings announced are higher than earnings forecast. I also examine whether *Sentiment*, which is the polarity score of tweets, intensifies the influence that *Average Controversy* has on *CAR*. Control variables are defined in Appendix B and the test results are in Table 8.

[9] In untabulated results, I tested the influence of short-term controversy level, which is the last 90 days' average controversy in the tweets level on CARs associated with earnings announcement events. The results were insignificant, implying that it is only a firm's persistent, as opposed to short-term, controversy level in tweets that influences how investors react around earnings announcement events.

Firstly, *Average Controversy* exhibits a highly significant positive association with abnormal returns, signifying that the controversy level surrounding earnings announcements has a substantial positive effect on *CAR* (β = .01). Moreover, *Good News,* indicating actual earnings are higher than forecasted earnings, demonstrates a statistically significant positive relationship with *CAR* (β = 0.02). This implies that positive news leads to higher abnormal returns. Interaction effect of *Average Controversy* × *Good News* exhibits a reduced positive impact on *CAR* (β = 0.001), which implies that firms' average controversy level can lessen the positive abnormal returns around good earnings news. I find no significant impact of *Sentiment* in this test.

[INSERT TABLE 8 HERE]

5.4.2 Investor Attention and the Effect of Controversial Tweets on Abnormal Returns

A likely explanation of the price distortion behavior I find in the main analysis is that by definition, controversial tweets have lower investor attention due to having low retweet counts. Previous studies show that investor attention is higher when retweet counts are higher (Nekrasov et al., 2021). I conjecture that the underlying cause for controversial firm tweets generating positive abnormal returns, contrary to the typical anticipation of negative repercussions from social media's "cancel culture," is rooted in diminished investor attention and the resulting information asymmetry (Blankespoor et al., 2014). To investigate this, I design a test with quartiles of retweet counts and examine the effect of controversial firm tweets on abnormal stock market returns for different levels of retweet counts. The regression results are in Table 9.

[INSERT TABLE 9 HERE]

The results reveal that controversial tweets are associated with significant positive abnormal returns for lower levels of retweet counts. Only for the fourth quarter of the retweet counts category did results show a significant negative effect on stock market returns. These results indicate that, due to a lower retweet count, which may result in lower investor attention, stock prices may only partially reflect the controversy inherent in the messages. Results also suggest that it is not solely the controversial nature of tweets posted by firms that establish the relationship between tweet response and stock market performance, but also the extent to which the information reaches the users matters.

6. Discussion and Conclusion

It is well established that tweets by firms and third parties can influence stock prices; less explored is the notion of controversial tweets. My paper explores firm tweets that are “ratioed” – tweets that have more replies than likes and retweets – and thus are seen as controversial by the Twitterverse. A significant relationship between controversial tweets and long-run abnormal market returns indicates that Twitter is not only a valuable source of information that firms use to disclose news to the public but that the level of controversy in firm tweets – as determined by the public’s response to firm tweets – can change the long-term performance of stocks.

The first hypothesis examines the impact of controversial firm tweets on long-run abnormal stock returns. The positive association between ratioed tweets and abnormal returns suggests that tweets considered controversial by the Twitterverse can positively influence stock prices. The finding challenges the conventional understanding that the wisdom of crowds in social media can predict a firm’s quarterly earnings and announcement returns (Bartov et al., 2018). The preliminary results indicate that social media discussions, even when heated, can benefit firms in terms of market valuation, a possible case of price distorting behavior of social media (Jia et al., 2020). Finally, the unexpected finding also hints towards social media-led stock trading by retail investors (Rakowski et al., 2021), which suggests that less-rational groups of investors are prone to behave according to their emotions (Baker & Wurgler, 2007; Barber et al., 2009; Kumar & Lee, 2006).

The second set of analyses delves deeper into the role of sentiment in the relationship between controversial tweets and market returns. The results show that the main effect of controversial tweets loses significance when sentiment is considered. Polarity has a significant negative association with abnormal returns, indicating that tweets with a positive sentiment tend to generate lower abnormal returns. The findings are consistent with the notion that overconfident firms are more exposed to stock market volatility (Rzeszutek et al., 2020) and stock price crash risk (Kim et al., 2015). However, the interaction term between ratioed tweets and polarity is positive and statistically significant. It suggests that when the positively oriented firm tweets get ratioed or otherwise receive traction within the platform, they can reverse the negative stock price effect. This nuanced finding highlights the importance of strategic disclosure by firms considering the influence of sentiment on social media.

One of the additional tests shows a substantial positive effect of average controversy around earnings announcement events, which implies that even controversy surrounding earnings news can lead to significant positive market reactions. However, the interaction effects between controversy and news suggest that the impact of controversy reduces the main positive effect of good news on stock returns. Lastly, another additional analysis shows the influence of retweet counts on the effects exerted by controversy in tweets on the stock market. The analysis posits a plausible rationale for the observed price distortion phenomenon in the primary findings of the paper.

The overall findings of the paper shed light on how firms can strategically leverage social media, including controversial content, to influence market perceptions and potentially enhance stock valuations. The study contributes significantly to the literature on social media's influence on financial markets, shedding light on the complex interplay between controversy, sentiment, and market returns.

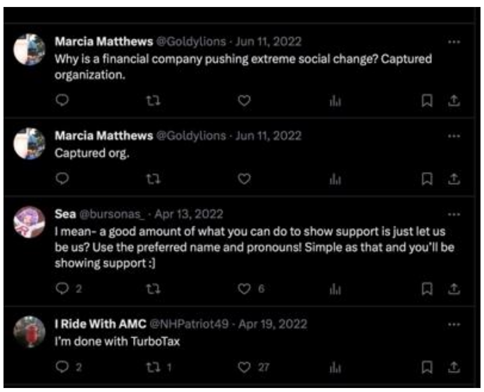
While this study provides valuable insights, the topic of controversial tweets has the potential to be advanced by investigating the timing of the controversial tweets to see if it confirms the “good news during, bad news after” hypothesis (Patell & Wolfson, 1982), which suggests that firms usually post good news during market hours and bad news after the market closes. Future studies can also investigate the consequences of controversial firm tweets for CEOs regarding their compensation or hire/fire decisions. Finally, controversy can be explored to see if it has a consequence for other business outcomes such as, sales, credit rating, reputation etc.

Appendix B: Variable Definition

Variable	Description
Returns Variables	
Abnormal Returns	The difference between annual value-weighted returns of the stock and returns on the S&P 500 Index
CAR	Cumulative abnormal returns [t_0, $t_{+}1$], with expected returns based on a market-adjusted model calculated over the [-100, 0] pre-earnings announcement period
Controversy Variables	
Ratioed Tweet	Coded as 1 if the annual average replies-to-retweet ratio is greater than 1
Ratioed tweet Score	The average replies-to-retweet ratio of firm-tweets in a given year
Average Controversy	Average ratio of replies-to-retweet ratios greater than 1 in the year t-1
Earnings Announcement News	
Good News	Coded as 1 if earnings surprise is positive, else 0
Tweet-sentiment values	
Polarity	Annual average polarity score for firm tweets
Subjectivity	Annual average subjectivity score for firm tweets
Sentiment	Annual average polarity score for firm tweets
Control Variables	
Firm Size	Log of total assets
Book-to-Market	The ratio of book value to market value
Return on Assets	The ratio of net income/loss to total assets
Institutional Ownership	% of outstanding shares held by institutional owners
Media Coverage	Number of *Wall Street Journal a*rticles on firms
Analyst Followings	Number of analyst recommendations (I/B/E/S)
Returns Trend	Cumulative abnormal stock returns for 20 days preceding the earnings announcement date

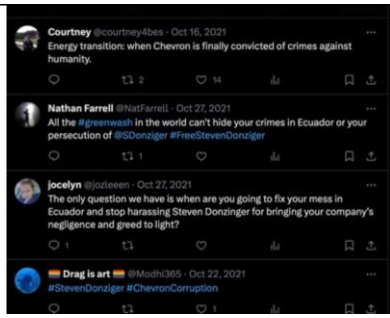
Table 1: Examples of highly ratioed firm tweets

<table>
<tr><td>Tweet</td><td>Replies to retweet ratio</td><td>Source</td></tr>
<tr><td>Do you want to be an ally for the trans+ community but don’t know where to start? To help you on that quest, here are 10 ways to show your support for transgender and non-binary people from our 3rd annual Trans+ Summit.


</td><td>86</td><td>https://twitter.com/Intuit/status/1509982953035616261</td></tr>
<tr><td>We can respond to your tax notices for you and represent you in case of an audit, even if we didn’t do your taxes. Why go it alone? Get help today</td><td>84</td><td>https://twitter.com/HRBlock/status/1355168875143421956</td></tr>
</table>

<table>
<tr><td>
</td><td></td><td></td></tr>
<tr><td>In the Americas, we are excited to welcome over 200 students to the 2021 Summer Intern Class! Due to COVID-19, the internship is virtual again this summer. Students will gain skills & knowledge to help them kickstart their careers & build a strong foundation for the future.


</td><td>71</td><td>https://twitter.com/blackrock/status/1402711741566443524</td></tr>
<tr><td>It's only human to have questions about the energy transition. Luckily, the human energy company has answers.</td><td>60</td><td>https://twitter.com/Chevron/status/1448997136461348901</td></tr>
</table>

<table>
<tr><td></td><td></td><td></td></tr>
<tr><td>One of our top priorities as a company is keeping our associates and customers safe. Hear from associates across the Kroger family on their Why when it comes to supporting each other by wearing a mask and following safety protocols. What's your Why?

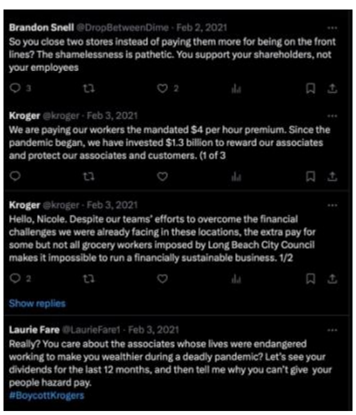
</td><td>45</td><td>https://twitter.com/kroger/status/1355274645990215688</td></tr>
</table>

Table 2: Data and Sample Selection

Panel A: Sample to test H1 and H2

	# of firms	Number of observations
Annual average firm tweet controversy between 2020-2022	440	1,539
Annual average firm tweet controversy merged with COMPUSTAT and Factiva data for 2020 and 2021	220	621
Less: Missing Book-to-Market and Institutional Ownership values		(107)
Final Sample	220	514

Panel B: Sample to test market reaction to average tweet controversy around earnings announcements

	# of firms	Number of observations
Quarterly earnings announcements between 2020-2022	506	6,072
Firm-year average tweet controversy merged with earnings announcements	506	6,072
Earnings announcement-tweet controversy data merged with Factiva and COMPUSTAT data	502	5,822
Less: Missing observations		(2,847)
Final Sample	322	2,497

Table 3: Descriptive Statistics

Panel A: Descriptive statistics of the variables in equations 1 and 2 for testing hypotheses 1 and 2

	N	Mean	SD	Min	Max
Abnormal Returns	514	-.0015	0.0091	-.01027	0.0079
Ratioed Tweet	514	.2082	0.4063	0	1
Firm Size	514	10.1511	1.2253	7.3570	15.1355
Book-to-Market	514	0.0012	0.0019	-0.0057	0.0203
Return on Assets	514	0.0573	0.0892	-0.3812	0.5110
Institutional Ownership	514	0.8377	0.2810	0.000	3.0883
Media Coverage	514	10.0196	27.6607	0	300
Analyst Following	514	18.3307	7.1723	1	50
Polarity	514	0.1764	0.0831	-0.0992	0.8
Subjectivity	514	0.3888	0.1028	0	1

Panel A presents descriptive statistics for 514 firm-year observations. It includes mean, median, standard deviation, minimum, and maximum values of the dependent variable, Abnormal Returns; the independent variable, Ratioed Tweet (categorical variable showing whether the average tweet replies surpass average retweet counts in a firm year); and other control variables defined in Appendix B.

Table 3: Descriptive Statistics
Panel B: Correlation Matrix

	Ratioed Tweet	Firm Size	Book-to-Market	Return on Assets	Institutional Ownership	Media Coverage	Analyst Following	Polarity	Subjectivity
Ratioed Tweet	1								
Firm Size	0.1024*	1							
Book-to-Market	0.0067	-0.1184*	1						
Return on Assets	-0.1290	-0.3141*	-0.0300	1					
Institutional Ownership	-0.0260	-0.1560*	0.0071	0.0275	1				
Media Coverage	0.0058	0.4160*	-0.1551*	-0.0789	-0.1717*	1			
Analyst Following	0.0703	0.2815*	-0.2839*	0.0154	-0.0120	0.3301	1		
Polarity	-0.0803	0.0990	0.0552	-0.0469	-0.0058	0.0414	0.0372	1	
Subjectivity	0.0440	-0.0384	0.0765	-0.0298	-0.0232	-0.0514	-0.0630	0.1054	1

Panel B reports pairwise correlation coefficients between all variables used in the hypothesis tests. All variable definitions are included in Appendix C.

Table 3: Descriptive Statistics

Panel C: Descriptive statistics of the variables to test market reaction to average tweet controversy around earnings announcement events

	N	Mean	SD	Min	Max
CAR	2,497	-0.0005	0.0583	-0.3343	0.3180
Average Controversy	2,497	3.6969	4.7173	1.2444	90.5
Good News	2,497	0.7201	0.4491	0	1
Sentiment (Polarity)	2,497	0.1952	0.1503	-0.3333	1
Firm Size	2,497	10.5038	1.3450	7.3095	15.1356
Media Coverage	2,497	12.1282	27.6986	0	300
Institutional Ownership	2,497	0.8142	0.2595	0	3.0084
Returns Trend	2,497	0.0053	0.0822	-0.4267	0.3832

Panel C presents descriptive statistics for 2,497 firm-earnings announcement event observations. It includes mean, median, standard deviation, minimum, and maximum values of the dependent variable *CAR*, independent variable, *Average Controversy,* and other control variables defined in Appendix B.

Table 4: Controversial Firm Tweets and Abnormal Returns *(Test of H1)*

	Abnormal Returns
Ratioed Tweet (Ratioed =1, Not-ratioed =0)	0.01^{**}
	(0.0008)
Firm size	-0.002^{**}
	(0.0006)
Book-to-Market	-0.2
	(0.3)
Return on Assets	-0.04^{**}
	(0.007)
Institutional Ownership	-0.003^{**}
	(0.001)
Media Coverage	0.00002
	(0.00002)
Analyst Followings	-0.00007
	(0.00009)
Industry fixed effects	Yes
Constant	0.02^{**}
	(0.006)
Observations	514
Adjusted R^2	0.039

Table presents results from regression of equation (1), where the dependent variable *Abnormal Returns* is the annual abnormal market returns for S&P500 firms. Control variables are as defined in Appendix B. Standard errors are clustered at the firm level and are shown in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 5: Sentiment of Controversial Firm Tweets and Abnormal Returns *(Test of H2)*

Panel A: Polarity and Abnormal Returns (H2a)

	Abnormal Returns
Ratioed Tweet	0.001
	(0.002)
Polarity	-0.01^{**}
	(0.003)
Ratioed Tweet × Polarity	0.005^{*}
	(0.002)
Firm Size	-0.002^{**}
	(0.0005)
Book-to-Market	-0.08
	(0.2)
Return on Assets	-0.04^{**}
	(0.006)
Institutional Ownership	-0.002^{*}
	(0.001)
Media Coverage	0.00001
	(0.00002)
Analyst Followings	-0.0001
	(0.00010)
Industry fixed effects	Yes
Constant	0.03^{**}
	(0.006)
Observations	514
Adjusted R^2	0.140

Table presents results from regression of equation (2a), where the dependent variable *Abnormal Returns* is the annual abnormal market returns for S&P500 firms. Control variables are as defined in Appendix B. Standard errors are clustered at the firm level and are shown in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 5: Sentiment of Controversial Firm Tweets and Abnormal Returns (Test of H2)
Panel B: Subjectivity and Abnormal Returns (H2b)

	Abnormal Returns
Ratioed Tweet	0.010*
	(0.004)
Subjectivity	-0.003
	(0.008)
Ratioed Tweet × Subjectivity	0.002
	(0.009)
Firm Size	-0.002**
	(0.0006)
Book-to-Market	0.05
	(0.3)
Return on Assets	-0.04**
	(0.007)
Institutional Ownership	-0.004*
	(0.001)
Media Coverage	0.00002
	(0.00002)
Analyst Followings	-0.00006
	(0.000009)
Industry fixed effects	Yes
Constant	0.02**
	(0.006)
Observations	514
Adjusted R^2	0.028

Table presents results from regression of equation (2b), where the dependent variable *Abnormal Returns* is the annual abnormal market returns for S&P500 firms. Control variables are as defined in Appendix B. Standard errors are clustered at the firm level and are shown in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 6: Ratioed Tweet Score and Abnormal Returns *(Robustness test of H1)*

	Abnormal Returns
Ratioed Tweet Score	0.006**
	(0.001)
Firm size	-0.002**
	(0.0005)
Book-to-Market	-0.08
	(0.2)
Return on Assets	-0.04**
	(0.006)
Institutional Ownership	-0.003**
	(0.001)
Media Coverage	0.00001
	(0.00002)
Analyst Followings	-0.0001
	(0.00009)
Industry fixed effects	Yes
Constant	0.02**
	(0.006)
Observations	514
Adjusted R^2	0.129

Table presents results from the regression of equation (1), with the independent variable replaced by a new variable, *Ratioed Tweet Score*, which captures the ratio of controversial tweets. The dependent variable, *Abnormal Returns*, is the annual abnormal market returns for S&P500 firms. Control variables are as defined in Appendix B. Standard errors are clustered at the firm level and are shown in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 7: Propensity Score Matching

Panel A: Treatment Effect (treatment = Ratioed Tweets, control = Not-ratioed Tweets

	Abnormal Returns				
	Nearest neighbour matching	Mahalanobis matching	Radius matching (0.02)	Kernel matching	Stratification matching
Ratioed Tweet	0.0056**	0.0102**	0.009**	0.009**	0.008**

Panel B: Covariate Descriptive Statistics and Tests of Differences in matched sample

	Treatment Mean	Control Mean	%bias	t-test	P > |t|
Firm Size	10.227	10.194	2.7	0.66	0.507
Book-to-Market	0.00139	0.00145	-3.1	-0.73	0.468
Return on Assets	0.04062	0.04384	-3.1	-0.77	0.441
Institutional Ownership	0.84928	0.84914	0.0	0.01	0.991
Media Coverage	8.3096	10.424	-9.1	-1.93	0.054
Analyst Followings	18.578	19.48	-12.4	-2.97	0.003**

Table presents propensity-scored matched sample analysis, where the treatment group constitutes firm tweets that have higher replies than retweets (ratioed), and the control group contains firm tweets that have rely lower than retweets (not-ratioed) on. Panel A shows the average treatment effect *Ratioed Tweets* on the treated for various matching techniques. Panel B shows the mean differences amongst the control variables in equation (1) for a matched sample based on the nearest neighbor matching. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 8: Market Reaction to Average Tweet Controversy Level Around Earnings Announcement Events

	CAR
Average Controversy	0.01^{**}
	(0.0007)
Good News	0.02^{**}
	(0.006)
Sentiment	-0.01
	(0.02)
Average Controversy × Good News	0.001^{+}
	(1.0006)
Good News × Sentiment	0.02
	(0.03)
Average Controversy × Good News × Sentiment	-0.003
	(0.003)
Firm Size	0.0004
	(0.001)
Institutional Ownership	-0.008^{*}
	(0.003)
Media coverage	-0.0002^{*}
	(0.00007)
Analyst Followings	-0.00005
	(0.00007)
Returns Trend	0.2^{**}
	(0.02)
Industry fixed effects	Yes
Constant	-0.01
	(0.02)
Observations	2497
Adjusted R^2	0.118

Table presents results from regression of equation (3), where the dependent variable *CAR* is the Cumulative Abnormal Returns generated from earnings announcement news for S&P500 firms. Control variables are as defined in Appendix B. Standard errors are clustered at the firm level and are shown in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 9: Investor Attention and the Effect of Controversial Tweets on Abnormal Returns

	Abnormal Returns
Ratioed Tweet	0.006**
	(0.002)
Second Quartile of Retweet Counts	0.005**
	(0.0010)
Third Quartile of Retweet Counts	0.01**
	(0.001)
Fourth Quartile of Retweet Counts	0.02**
	(0.001)
Second Quartile of Retweet Counts × Ratioed Tweet	0.006**
	(0.002)
Third Quartile of Retweet Counts × Ratioed Tweet	-0.002
	(0.0002)
Fourth Quartile of Retweet Counts × Ratioed Tweet	-0.004*
	(0.002)
Firm size	-0.002**
	(0.0004)
Book-to-Market	0.4**
	(0.1)
Return on Assets	-0.02**
	(0.006)
Institutional Ownership	-0.002**
	(0.0007)
Media Coverage	0.00002
	(0.00002)
Industry fixed effects	Yes
Constant	0.01**
	(0.005)
Observations	519
Adjusted R^2	0.477

Table presents results from regression, where the dependent variable *Abnormal Returns* is the annual abnormal market returns for S&P500 firms. Control variables are as defined in Appendix B. Standard errors are clustered at the firm level and are shown in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Chapter Four: Does City Crime Influence Accounting Misconduct by Firms?

1. Introduction

Fraudulent financial reporting harms investors and creditors through misleading financial statements (Elliot & Willingham, 1980), representing a crime costing over $300 billion USD per year (Bruce, 2020).[10] What drives firms to engage in this behavior? Previous literature on the determinants of fraudulent financial reporting mainly documents characteristics of firms and of employees (Caskey & Hanlon, 2013; Cline et al., 2018; Davidson et al., 2020; Dechow et al., 2011; Kim et al., 2012; Law & Mills, 2019). Less explored as a driver of fraudulent reporting is the impact of macro-level social and environmental factors such as *crime* (Bates & Robb, 2008; Hipp et al., 2019; Parsons et al., 2018; Rosenthal & Ross, 2010; Sacerdote & Scheinkman, 1996; Sloan et al., 2016). The economics literature has shown crime to have considerable and various impacts on businesses. In this study, I extend such research by examining how crime levels in the external environment influence firms' decisions to engage in fraudulent financial reporting. Consistent with the notion that neighborhood crime, due to social norms and culture, influences peoples' decision to break the rules (Sacerdote & Scheinkman, 1996), I posit that crime in a city will likewise influence business leaders' decision to break the rules, which will ultimately manifest in determining whether or not firms commit accounting fraud.

To test this idea, I investigate whether city-level crime rates in the U.S. affect the likelihood of enforcement actions related to accounting fraud issued by the Securities and Exchange Commission (SEC). Specifically, as a proxy for firms that are engaging in fraudulent activity, I collect data from Dechow et al. (2011)[11] on the SEC's Accounting and Auditing Enforcement Releases (AAERs) (Brown et al., 2020; Lennox & Pittman, 2010; Purda & Skillicorn, 2015). Combining this data with city-level crime rate data from the FBI's Uniform

[10] ACFE's (Association of Certified Fraud Examiners) 2020 Report to the Nations is based on 2504 real cases of occupational fraud from 125 countries, and it explores the costs, schemes, victims, and perpetrators of fraud.
[11] AAER dataset currently consists of 4,012 AAERs, covering 1,657 firm misstatements, issued between the year 1982 and 2018 (https://sites.google.com/usc.edu/aaerdataset/home). For my paper, I have investigated years 2002 to 2018, which has total 1164 fraud data for 374 firms.

Crime Reporting Program (*Crime Data Explorer*, 2023),[12] my sample constitutes 33,663 firm-year observations from 2002 to 2018.

In the main hypothesis test, the dependent variable is *Fraud*, which takes the value of 1 when a firm has received an AAER from the SEC for likely fraud in a year, and 0 otherwise. I presume there could be a possibility of reverse causality as research shows fraud detection can detrimentally impact society and crime in the neighborhood (Holzman et al., 2021). Therefore, as the independent variable, I measure *City Crime* as the one-year-lagged crime rate in the city where firms are headquartered. I run a set of additional tests to strengthen the paper's main argument. For example, I test the impact of variation in types of crime – particularly violent crime vs. property crime – on accounting misconduct. Moreover, with subsamples based on high versus low CEO compensation data, I analyze the variation of city crime's impact on fraudulent financial reporting, which complements the fraud-motivation literature in management (Efendi et al., 2007; Healy, 1985; Huang et al., 2012; Richardson & Waegelein, 2002). Finally, I show the proximity to SEC influences whether city crime increases the likelihood of accounting fraud. The overall findings of the paper implies that the higher the city crime rate, the greater the likelihood of accounting fraud.

My study adds to the existing literature on accounting fraud predictors and the growing literature on the relationship between neighborhood crime and accounting misbehavior. It is similar to the Cho et al. (2020) paper that argues regional crime impacts accounting behavior; however, my study examines likely fraud cases as opposed to earnings management and tax avoidance (Cho et al., 2020). Moreover, the current study shows that crime influences accounting fraud in firms, contrasting with the findings of Holzman et al. (2021), who documented that accounting frauds have a spillover effect on city crime. Finally, and more importantly, corporate fraud is crucial not only for academia but also for corporations and regulatory bodies due to its pernicious nature and associated costs. The most recent global survey on fraud by PWC (2020) revealed that around 56% of the respondents in their study mentioned they experienced fraud in the last 24 months, that it costs around US $42 billion, and that

[12] UCRP's *Crime in the United States* report contains a compilation of violent and property crime offences for the nation and state from the year 1995 to 2019. The report includes arrests, clearances, trends, and law enforcement employee data. For my paper, I investigate years 2001 to 2017 as the fraud data is available from 2002 to 2018.

accounting fraud is one of the top three frauds reported.[13] My paper adds to policy decisions by focusing on the city crime rate as an additional fraud predictor. The findings are, therefore, relevant and valuable for the regularity and policy-making institutions in curbing accounting fraud.

This paper continues as follows. Section two covers the literature review and hypothesis development. Section three describes the research design and data. Section four reports an analysis of findings, and section five discusses the results and concludes.

2. Literature Review and Hypothesis Development

2.1 Accounting and Auditing Enforcement Releases

Corporate crime is interchangeably labelled as corporate fraud, economic and profit-driven crime, and white-collar crime (Naylor, 2017). The SEC issues AAERs to communicate to the public about financial reporting-related enforcement actions concerning civil lawsuits brought by the Commission, notices and orders concerning the firms, and settlement of administrative proceedings. The SEC's website includes AAERs issued from 1999 to the present.[14]AAERs are enforcements that are usually financial reporting and audit related misconducts in which the nature of the misconduct, the people and entity involved, and the impact on financial statements are included. To find what predicts material accounting misstatements by a firm, Dechow et al. (2011) developed a dataset of SEC-issued AAERs and analyzed the firm characteristics of misstating firms to identify what factors can predict misstatements. Consequently, many research scholars have utilized these enforcement releases as proxies for accounting misstatement (Brown et al., 2020), audit quality (Markelevich & Rosner, 2013), and fraud (Lennox & Pittman, 2010; Purda & Skillicorn, 2015). Prior studies have found significant relationships between AAER disclosures and adverse market returns (Christensen et al., 2010; Nourayi, 1994). Nourayi (1994) first documented the detailed process of enforcement actions taken by the Commission and the effect of the announcement of these investigations on the stock market. The litigation releases had been found to downgrade stock prices when companies were charged significantly. The effect is more substantial for more severe violations, which suggests AAERs are value-relevant for the capital markets and, as such, are good proxies

[13] PwC surveys US and global executives of corporations to uncover timely and data-driven crime trends, the cost of frauds, perpetrators, and what companies are doing to deter crimes.
[14] https://www.sec.gov/divisions/enforce/friactions.htm

of accounting fraud. Although many firms may go unidentified by the SEC as these investigations are time-consuming and costly, the fact that the SEC would only release AAERs in cases where they have detected some misconduct, reducing the Type I error of finding false positives (Dechow et al., 2011).

2.2 Neighborhood Crime and Influence on Business

The relationship between crime in cities and business is reciprocal. While it is argued that crime increases following retail openings in an area, it is also documented that businesses follow crime rates and prefer locating in areas where the crime rate is low (Rosenthal & Ross, 2010). I am interested in the effects of crime on businesses, and the literature notes several types of impacts. Bowes (2007) found evidence that suggests high crime in a neighborhood discourages business development as it may increase business costs, business crime, and fear of crime that drives away customers. Hipp et al. (2019) argue that high crime in a city is associated with business failure and mobility, reducing the likelihood that businesses will locate there. Other studies have found that the economic impacts of neighborhood crime include lower property values (Lens & Meltzer, 2016) and decreased operating performance (Hua & Yang, 2017).

2.3 Accounting Misconduct and Its Determinants

Previous literature on fraudulent financial reporting, also known as accounting misconduct, has examined a broad range of areas, including the motivation behind the fraud (Bens et al., 2012), "red flags" or indicators of likely fraud (Bao et al., 2020; Beasley, 1996; Bonner et al., 1998; Brown et al., 2020; Summers & Sweeney, 1998), the consequences of fraud disclosures (Bowen et al., 2010), and the role of regulators (Berger & Lee, 2022; Hail et al., 2018) and the media (Miller, 2006).

As for the predictors of accounting fraud, one mainstream research has focused on how various firm-specific characteristics influence accounting misconduct or financial reporting fraud. In a study investigating the restated financial statements at the end of the 1990s market bubble, Efendi et al. (2007) documented that firms are more likely to misstate financial statements when their CEOs have in-the-money stock options and serve as a board chair that raises new capital and is constrained by interest-coverage debt covenants. Christensen et al. (2015) investigated factors associated with the likelihood that a firm will be investigated by the SEC. They found that prior year abnormal accruals, return on assets, and Altman Z score are successful indicators of the SEC exploring a firm and finding it fraudulent. Dechow et al. (2011) examined the characteristics of misstating firms who had received AAERs and found that at the time of misstating, firms have low accrual and deteriorating non-financial performance measures, that managers of misstating firms are sensitive to their firms' stock prices, and that they cover up financials to maintain high stock market valuation. Based on a sample of firms that were issued AAERs by the SEC, Markelevich and Rosener (2013) showed evidence that suggests that fraud firms pay, on average, higher audit fees. Another predictive variable found in the literature is dividend policy; Caskey and Hanlon (2013) highlight that dividend-paying status is negatively associated with AAER firms, indicating that dividends can constrain financial misreporting. Other indicators of fraud firms include a lack of engagement in socially responsible activities, honesty, trustworthiness, and prudence in financial reporting (Kim et al., 2012).

Management's involvement in crime is also explored in the fraud literature (Cline et al., 2018; Davidson et al., 2020; Law & Mills, 2019). Cline et al. (2018) argue that firms with executives who have been accused of dishonesty, violence, abuse, and sexual misadventure suffer from lower operating performance and market value. Law and Mills (2019) argue financial advisors with pre-advisor criminal records are 32% more likely to experience customer complaints and more serious allegations of financial crime, such as unsuitable investment, unauthorized transactions, etc. Using executives' criminal records, studies found evidence that executives with records earn higher abnormal returns while trading on inside information (Davidson et al., 2020), and that the likelihood of bankruptcy is positively associated with employees' criminal records and that they increase the cost of debt for those employer firms (Regenburg & Seitz, 2021)

I am interested in another dimension of crime: the influence of crime rates in the business environment. The existing literature provides strong preliminary support for connecting crime rates and fraud. Most notably, a recent research study by Cho et al. (2020) examined the borough-level crime rate in London from 2006 to 2013 and corporate reporting by private firms. It concluded that crime influences earnings management and tax avoidance. The authors specifically argue that managers exposed to criminal incidents will eventually be less worried about the social stigma and engage in opportunistic behaviors, which plays a significant role in shaping corporate reporting behavior. Earnings management and tax avoidance are only two tools by which management can tweak accounting numbers. In contrast, the scope of AAERs is much broader, encompassing accounting misconducts such as false and misleading statements, financial records, internal controls, improper professional conduct, and audit deficiencies (Ferullo, 2019). My study investigates the AAERs firms have received from the SEC after detecting accounting misconduct (Holzman et al., 2021), making the relationship between social crime and corporate fraud more prominent. Furthermore, unlike Cho et al. (2020), who investigated private firms, I examine the public firms that are exposed to more scrutiny by the regulatory authority, SEC.

Holzman et al. (2021), using the FBI crime dataset and AAERs, documented that after accounting misconduct is revealed by the SEC through AAERs, there is an increase in financially motivated neighborhood crime, such as robberies, theft, etc., in the area where the firms are headquartered. I assume the relation is likely more salient in the reverse direction: Accounting fraud may likely rise due to an increase in the crime rate in the neighborhood where the corporate headquarter is situated. I state my hypothesis in the following form:

Hypothesis: Accounting fraud increases with the crime rate in the city where the firm is headquartered.

3. Research Design and Data

I use the following equation to test the relationship between city crime rates and accounting fraud committed by firms headquartered in the city:

$$Fraud_{it} = \beta_0 + \beta_1 City\ Crime_{ijt-1} + controls_{it} + \varepsilon_{it} \ldots\ldots\ldots(1)$$

The level of analysis is the firm-year. The dependent variable, *Fraud*, is a categorical variable that measures whether a firm *i*, in a given year *t*, received an AAER from the SEC. The main independent variable, *City Crime*, is the city-year level crime rate for city *j*, in which firm *i* is headquartered in year *t-1*. I use logistic regression to test the relationship between the independent and the dependent variable. I presume that the regression model testing the relationship between crime and fraud may be subject to potential endogeneity as many confounding factors could influence the likelihood of receiving AAERs by a firm. The firm-level controls I use in my equation are borrowed from the literature that found evidence of firm-level determinants affecting accounting misconduct or corporate misreporting. The controls include *Firm Size*, *Book-to-Market, Loss, and Leverage* (Berger & Lee, 2022; Dechow et al., 2010; Efendi et al., 2007; Erickson et al., 2006; Lennox & Pittman, 2010). Furthermore, I incorporate industry-year fixed effects to account for factors such as legislative actions and regulations enacted in different years, which may have varied impacts on reporting behaviors across industries. I cluster standard errors at the firm level following Berger and Lee (2022).

The crime statistics are collected from the FBI's Uniform Crime Reporting Program and AAER data from the University of Southern California's website (Dechow et al., 2011). All other firm-level variables are collected from COMPUSTAT in WRDS. First, I collected firm-level financial data for the years 2002 to 2018 from WRDS; next, I merged the AAER data using a firm identifier and measured the categorical dependent variable, *Fraud*. Finally, I collected the offences data from FBI's UCRP dataset and calculated the independent variable, *City Crime*, for the cities in the USA, by dividing the number of offences reported by population in the city. I merged the crime data and firm-level financial and fraud data by the city and state the firms are headquartered in. After merging datasets and excluding missing observations, my data sample has 33,663 firm-year observations from 2002 to 2018. Details of sample selection are in Table 1. I have collected the firm controls from COMPUSTAT. For additional analysis with CEO-level data, I have collected CEO compensation variables from EXECUCOMP. To measure the distance between SEC's headquarter and the firms' for another additional test, I have collected zip code data from Simplemaps. Appendix C contains definitions for the dependent, the independent, and the control variables.

[INSERT TABLE 1 HERE]

5. Analysis of Findings

5.1 Descriptive Statistics

Figure 1 shows the trend in the average city crime rate in the U.S over the years. The graph indicates that crime has an overall downward trend, and that it dropped significantly after the year 2015.

[INSERT FIGURE 1 HERE]

In Table 2, panel A, I show the changes in the descriptive statistics of city crime over the years, distinguishing between two groups of firms in my sample – firms that received AAERs and those that did not. Notably, there is a contrast in the number of observations between these two groups, with a considerably higher count of non-fraudulent firms compared to fraudulent ones. Despite variations in the number of fraud and non-fraud firms, the city-crime rates remain similar for both groups; in certain years, locations with fraudulent firms even exhibit higher crime rates.

[INSERT TABLE 2 HERE]

Table 2, panel B describes the descriptive statistics of the variables in equation (1). *Fraud* has a relatively lower mean value of 0.0053, indicating that the number of fraudulent reporting instances is low. On the other hand, the mean value of *City Crime* indicates that, on average, the crime rate in the cities is 4.04%. Continuous control variables are presented in logged values; hence, the original numbers that are smaller than 0 are represented as negative. Consequently, the minimum values for *Firm Size, Book-to-Market*, and *Leverage* all have negative numbers.[15] Finally, *Loss*, with an average of 0.4604, reveals that instances of losses are prevalent in the data.

Panel C of Table 2 presents Pearson correlation coefficients for all variables in the main regression model. *City Crime* and *Fraud* have a positive significant correlation, while *City Crime* is positively (negatively) correlated with *Firm Size (Loss).* The correlation matrix and untabulated results of VIFs indicate there is no bias resulting from multicollinearity.

5.2 Effect of City Crime on Fraudulent Financial Reporting

Table 3 presents the results of logistic regressions testing the relationship between the city crime rate and accounting fraud. The coefficient estimate reveals that *City Crime* has a positive and significant relationship with *Fraud*. I interpret the parameter coefficients from Table 3. Specifically, column 1 of Table 3 suggests that for every one-unit increase in the city's crime rate, the log-odds of a fraud case increase by 9.6.[16] The findings also show *Firm Size* is a significant control, suggesting larger firms are more likely to engage in fraud. On the other hand,

[15] For example, total asset is less than 1 for Askmenow Inc in 2005 and IDEXX Labs Inc. has negative book value per share.

[16] An odds ratio greater than 1 suggests an increase in the odds of the event. The odds ratio of 9.6 is $e^{\wedge 9.6}$ or 14764.78. The ratio represents multiplicative change in the odds of fraudulent financial reporting for a one-unit increase in City Crime.

Book-to-Market and *Loss* are not significantly associated with corporate fraud in my sample. *Leverage* shows a negative and significant relationship with accounting fraud, suggesting that companies with higher debts are less likely to engage in fraudulent reporting, perhaps due to more scrutiny by the lenders. Column 2 findings have similar inferences. While column 1 includes firm controls, column 2 shows results with industry-year fixed effects that control for industry-specific temporal influences, minimizing potential effects of confounding factors.

[INSERT TABLE 3 HERE]

5.3 Robustness Test

I presume unobservable variations in city characteristics could affect the relationship between crime rates and accounting behavior. I, therefore, re-run the main analysis with city fixed effects, and the findings remain consistent. Table 4 shows that the sign of the coefficient associated *City Crime* is positive and significant.

[INSERT TABLE 4 HERE]

5.4 Additional Analysis

5.4.1 Effect of Property Crime and Violent Crime on Fraudulent Financial Reporting

City Crime in the main sample includes both property crimes and violent crimes. In additional analysis, I test the variation of crime types and their impact on accounting misconduct. Fe and Sanfelice (2022) document that consumers respond more to property and street crime when deciding which food and entertainment venues to visit and how much time to spend there. Greenbaum and Tita (2004) argue that there is no direct relationship between violence and business activities as firms adapt to surges in violence within their operating environment. However, in contrast, Rosenthal and Ross (2010) documented that violent crime influences firms' decision to relocate as violent crime detrimentally impact businesses. Research also shows gun violence increases business deaths (Stacy et al., 2021). Results in Table 5 suggest, the effect of violent crime on the likelihood of accounting fraud is even greater than the effect of property crime.

[INSERT TABLE 5 HERE]

5.4.2 Effect of City Crime on Fraudulent Financial Reporting – High versus Low CEO Compensation

Early research on firms' motivation to commit accounting fraud argues that managers choose aggressive reporting to maximize compensation, wealth, bonus plans, equity grants, and equity holdings (Efendi et al., 2007; Healy, 1985). Richardson and Waegelein (2002) stress that bonus plans can be tied to earnings management. Building on this notion, I examine the variation in the effect of *City Crime* on *Fraud* for high CEO compensation and low CEO compensation, where the variable *compensation* includes salary, bonus, and all equity options and grants. I take subsamples based on the highest quartile and the lowest quartile of the average yearly CEO compensation for firms in my sample. Results are in Table 6.

Table 6 shows for low CEO compensation, there is no effect of *City Crime* on *Fraud*. For high CEO compensation, the relationship between *City Crime* and *Fraud* is positive and significant (β=18.9). These results suggest that the impact of the city crime rate on the likelihood of firms committing reporting fraud is amplified for firms that pay their CEOs relatively highly. The findings are consistent with Efendi et al. (2007) such that when CEO compensation is tied to the stocks, there is high chance of fraudulent financial reporting.

[INSERT TABLE 6 HERE]

5.4.3 Effect of City Crime on Fraudulent Financial Reporting – Geographical proximity to the SEC

Finally, I investigate whether geographical distance between firm headquarters and the headquarter of the regulatory body, the SEC, is relevant. Kedia and Rajgopal (2011) document that the closer the firms are to the SEC, the greater prudence they exhibit in reporting behavior. To test the variation in the effect of *City Crime* on *Fraud*, I take two subsamples based on the distance between firm headquarters and the SEC. I measure the *distance* variable by using a custom Python code that utilizes the coordinates (latitudes and longitudes) of the zipcodes I collected from Simplemaps (*US Zip Codes Database*, 2023). I take the subsamples of observations based on the lowest quartile and the highest quartile of the *distance* variable and re-run the baseline regression model for both the subsamples.

Findings in Table 7 show that the *City Crime* has no significant impact on *Fraud* when the SEC is farther from the firm headquarters, whereas there is a positive significant association between the rise in *City Crime* and *Fraud* (indicating firms receive more AAERs from the SEC) when the SEC headquarter is closer to the firm headquarters. This contradicts the argument that proximity to the regulatory body can make firms more compliant (Kedia & Rajgopal, 2011). Although cost constraint is not a direct indicator of how the SEC decides which firms to investigate, and I do not make an argument about the association between proximity and fraud, the unconventional result that I find with the subsample analysis complements the notion that, relative to all firms that announce restatements, the SEC is more likely to investigate a firm that is in close proximity due to cost constraints (Kedia & Rajgopal, 2011). This could be the reason why I find results indicating a positive association between city crime and accounting fraud for firms that are in close proximity to the SEC headquarters. These results offer valuable insights into the way geographic positioning can intricately shape the extent and magnitude of crime rate impacting fraudulent accounting practices.

[INSERT TABLE 7 HERE]

6. Discussion and Conclusion

Accounting misconduct is a big area in accounting and finance research. Understanding the sensitivity of accounting behavior to local crime is crucial for businesses, city planners and policymakers. This paper adds value to the determinants of accounting fraud literature while also contributing to the criminology literature as it ties city crime rates to firm-level misconduct. The main hypothesis test suggests that the higher the city's crime rate, the higher the likelihood of accounting fraud in that city. The findings indicate crime as one determining factor in why firms engage in fraudulent financial reporting. My findings complement what Cho et al. (2020) found with London Borough crime investigating earnings management. Unlike Holzman et al. (2021) the paper also suggests that the relationship between neighborhood crime and corporate fraud can be reversed – that crime can be a determining factor and not just a consequence of detected accounting fraud.

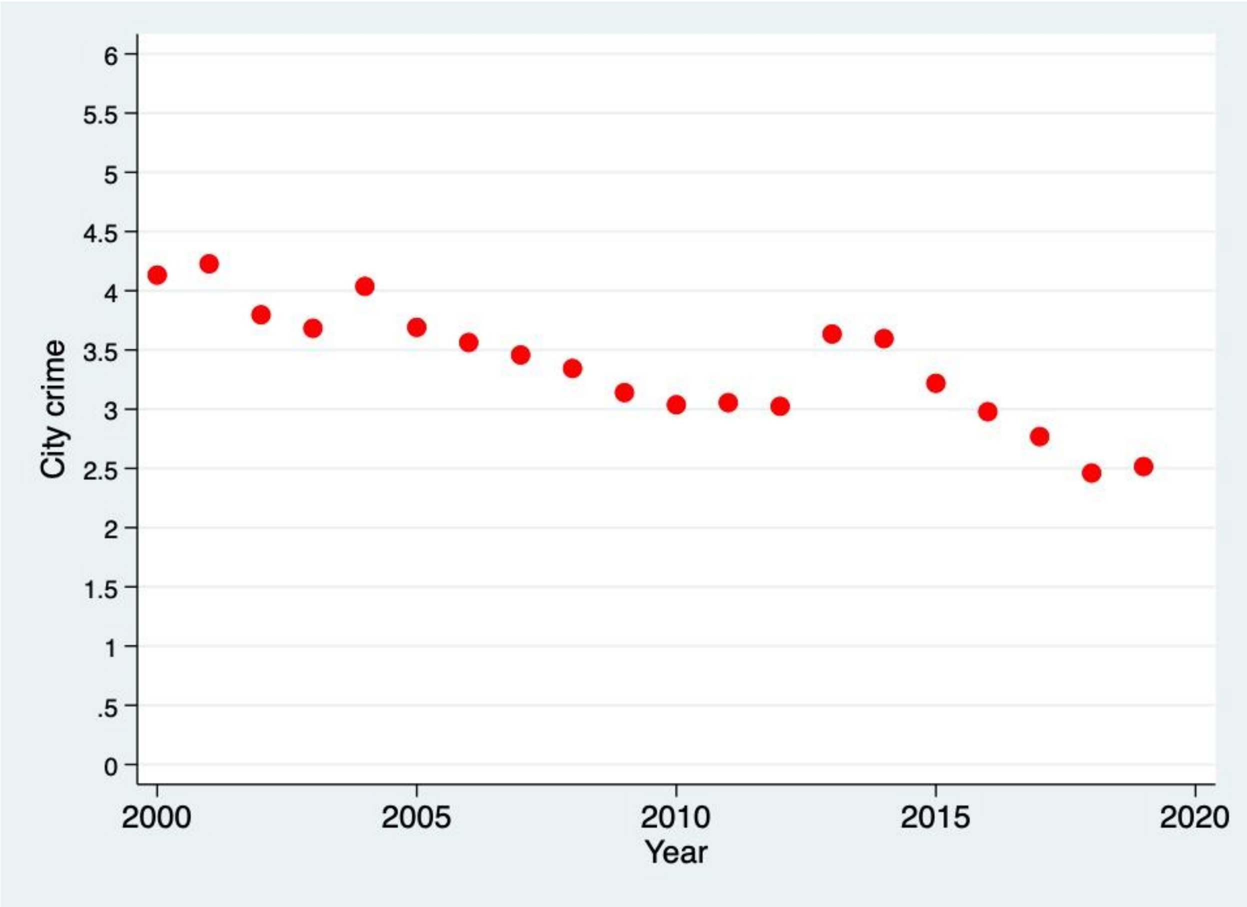
Further analysis shows that both property crime rate (Fe & Sanfelice 2022), and violent crime rate influence accounting behavior, however, violent crime impacting more, which is consistent with Rosenthal and Ross (2010). I also find evidence that for firms with high CEO compensation, high crime rate in the city increases the likelihood of those firms committing accounting fraud. The findings align with the argument that managers commit corporate fraud when it maximizes their wealth (Efendi et al., 2007; Healy, 1985). Finally, additional findings reveal proximity to regulatory authorities is relevant in the manner in which city crime influences firms receiving AAERs from the SEC due to likely accounting fraud.

These findings open up future avenues of research in this area. Criminology research shows that crime in suburban areas motivates people to migrate. This aligns with the "flight from blight" theory of Bradford et al. (1973); I assume that city crime may force firms to move out of the city and change headquarters locations. Future research can explore the change in headquarters location and examine the effect of the shift on accounting misconduct or financial mis(reporting). Future studies can also explore the impact of crime by categories of sex, age, income, education and other demographics on firm-level outputs. Executive-level criminal records can be further explored to see their impact on firm governance and internal control. Capital market studies can be designed around the AAER issue date, especially the variation of the market reaction to AAER events based on geographic crime differences. Research on the relationship between macro-environmental factors, city crime, and firm-level accounting misconduct is still growing, and this paper sheds some light on the matter by offering empirical evidence.

Appendix C: Variable Definitions

Variable	Description
Dependent Variable	
Fraud	Coded as 1 if a firm receives AAER in a year
Independent Variable	
City Crime	Total offences, including property and violent crimes, divided by the total population in a city in a year
CEO Characteristics	
CEO Compensation	Total compensation (including salary bonus equity grants and options) of CEOs in a firm-year
SEC/regulatory body	
Distance	The geographical distance between the SEC's headquarter and firms' headquarters (in kilometers)
Control Variables	
Firm Size	Natural logarithm of total assets
Book-to-Market	Natural logarithm of book to market value of firms
Leverage	Natural logarithm of total debt to total equity
Loss	Coded as 1 if a firm has incurred a net loss in a given year

Figure 1: City Crime Rate Over Time



Note: Figure shows the average percentage point of city crime rates in the United States between the years 2000 and 2018

Table 1: Sample Selection

	# of Firms	# of observations
Firm-year data from WRDS	27,568	260,103
Firm-year data from WRDS merged with AAER data	27,568	260,103
Firm-Year-AAER data merged with City-crime data	16,241	113,966
Final sample excluding missing observations	5,997	33,663

Table 2: Descriptive Statistics

Panel A: City Crime for No-Fraud and Fraud Firms

	No-Fraud						Fraud					
	N	Mean	Median	SD	Pct_25	Pct_75	N	Mean	Median	SD	Pct_25	Pct_75
2002	123	0.0355	0.0270	0.0279	0.0156	0.0525	2	0.0207	0.0207	0.0089	0.0175	0.0238
2003	95	0.0386	0.0296	0.0343	0.0142	0.0530	1	0.0178	0.0178	NA	0.0178	0.0178
2004	2364	0.0510	0.0466	0.0253	0.0280	0.0718	28	0.0533	0.0468	0.0326	0.0234	0.0897
2005	2427	0.0522	0.0422	0.1293	0.0268	0.0706	21	0.0487	0.0456	0.0281	0.0260	0.0759
2006	2390	0.0507	0.0452	0.1182	0.0259	0.0670	17	0.0556	0.0549	0.0211	0.0375	0.0696
2007	2324	0.0486	0.0423	0.1142	0.0243	0.0658	14	0.0590	0.0623	0.0283	0.0270	0.0705
2008	2219	0.0469	0.0403	0.1151	0.0238	0.0605	9	0.0467	0.0463	0.0207	0.0299	0.0548
2009	2059	0.0438	0.0399	0.0865	0.0237	0.0632	8	0.0410	0.0315	0.0300	0.0240	0.0529
2010	2017	0.0413	0.0345	0.0869	0.0226	0.0561	11	0.0439	0.0391	0.0275	0.0285	0.0605
2011	1992	0.0417	0.0338	0.0699	0.0233	0.0574	8	0.0512	0.0455	0.0204	0.0353	0.0682
2012	1978	0.0410	0.0353	0.0689	0.0236	0.0560	13	0.0396	0.0415	0.0216	0.0278	0.0565
2013	2053	0.0374	0.0311	0.0199	0.0225	0.0521	13	0.0424	0.0391	0.0174	0.0274	0.0529
2014	1937	0.0368	0.0344	0.0196	0.0207	0.0518	10	0.0333	0.0371	0.0121	0.0245	0.0429
2015	1989	0.0344	0.0302	0.0186	0.0210	0.0452	8	0.0330	0.0290	0.0168	0.0219	0.0416
2016	1957	0.0335	0.0285	0.0183	0.0204	0.0436	11	0.0343	0.0315	0.0128	0.0227	0.0413
2017	1954	0.0332	0.0278	0.0181	0.0199	0.0446	4	0.0249	0.0222	0.0090	0.0186	0.0313
2018	1725	0.0303	0.0256	0.0171	0.0185	0.0419	2	0.0237	0.0237	0.0047	0.0204	0.0271

Table 2: Descriptive Statistics

Panel B: Variables to Test Main Hypothesis

	N	Mean	SD	Min	Max
Fraud	33,663	0.0053	.0729	0	1
City Crime	33,663	0.0404	0.0222	0	0.18873
Firm Size	33,663	6.3098	2.2833	-1.9732	14.4266
Book-to-Market	33,663	-4.6572	1.9128	-16.0914	16.0012
Loss	33,663	0.3593	0.4798	0	1
Leverage	33,663	-1.1307	2.0314	-7811	10.8444

Note: Continuous control variables are presented in logged values; hence, the original numbers that are smaller than 0 are represented as negative.

Table 2: Descriptive Statistics

Panel C: Correlation Matrix

	Fraud	City Crime	Firm Size	Book-to-Market	Loss	Leverage
Fraud	1					
City Crime	0.0166*	1				
Firm Size	0.0129*	0.0443*	1			
Book-to-Market	-0.0009	-0.0033	0.0048	1		
Loss	-0.0091	-0.0723*	-0.3926*	0.0075	1	
Leverage	-0.0007	0.0066	0.0084	0.0000	-0.0028	1

Panel C reports pairwise correlation coefficients between all variables used in the hypothesis tests. All variable definitions are included in Appendix C. * $p < 0.05$

Table 3: Effect of City Crime on Fraudulent Financial Reporting

	Fraud (1)	Fraud (2)
City Crime	9.6** (3.2)	9.2* (3.9)
Firm size	0.09* (0.04)	0.8^{+} (0.05)
Book-to-Market	-0.006 (0.04)	-0.02 (0.05)
Loss	-0.08 (0.2)	0.05 (0.1)
Leverage	-0.09** (0.03)	-0.04 (0.04)
Constant	-6.3** (0.3)	-4.7** (1.0)
Industry-year fixed effects		Yes
Observations	33,663	7,435

Table presents results of a logistic regression, where the coefficients are log-odds ratios. The dependent variable is the categorical variable, *Fraud*, which is equal to 1 if a company receives AAERS from the SEC due to the likelihood of fraud. Control variables are as defined in Appendix A. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 4: Effect of City Crime on Fraudulent Financial Reporting (Robustness Test)

	Fraud
City Crime	42.20** (11.2)
Firm Size	0.10+ (0.06)
Book-to-Market	-0.06 (0.07)
Loss	-0.04 (0.25)
Leverage	-0.002 (.05)
Constant	-1.6** (2.2)
Industry-year fixed effects	Yes
City fixed effects	Yes
Observations	2,779

Table presents results of a logistic regression, where the coefficients are log-odds ratios. The dependent variable is the categorical variable, *Fraud*, which is equal to 1 if a company receives AAERS from the SEC due to the likelihood of fraud. The models in this table include additional fixed effects, namely city fixed effects. Control variables are as defined in Appendix A. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 5: Effect of Property Crime and Violent Crime on Fraudulent Financial Reporting

	Fraud			
Property Crime	10.8**	10.14**		
	(3.6)	(4.08)		
Violent Crime			43.66**	42.1**
			(15.86)	(16.6)
Firm size	0.09*	0.08+	0.08+	0.07
	(0.04)	(0.04)	(0.04)	(0.04)
Book-to-Market	-0.005	-0.02	-0.004	-0.02
	(0.04)	(0.04)	(0.05)	(0.05)
Loss	-0.08	0.05	-0.10	0.04
	(0.2)	(0.18)	(0.18)	0.19
Leverage	-0.08**	-0.04	-0.09**	-0.04
	(0.03)	(0.04)	(0.03)	(0.04)
Constant	-6.3**	-4.7**	-6.1**	-4.5**
	(0.3)	(1.0)	(0.3)	(1.05)
Industry-year fixed effects		Yes		Yes
Observations	33,663	7,435	33,663	7,435

Table presents results of a logistic regression, where the coefficients are log-odds ratios. The dependent variable is the categorical variable, *Fraud*, which is equal to 1 if a company receives AAERS from the SEC due to the likelihood of fraud. Control variables are as defined in Appendix A. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 6: Effect of City Crime on Fraudulent Financial Reporting – High versus Low CEO Compensation

	Fraud	
	Sub-Sample Based on CEO Compensation	
	1st Quartile (Low Compensation)	4th Quartile (High Compensation)
City Crime	8.2	18.9*
	(8.7)	(8.8)
Firm Size	0.06	-0.2
	(0.4)	(0.1)
Book-to-Market	0.3	-1.3
	(0.2)	(1.4)
Loss	-1.2	0
	(0.8)	
Leverage	-0.2	-0.09
	(0.01)	(.06)
Constant	5.1*	-4.5**
	(2.2)	(1.5)
Observations	3,894	3,455

Table presents results of a logistic regression, where the coefficients are log-odds ratios. The dependent variable is the categorical variable, *Fraud*, which is equal to 1 if a company receives AAERS from the SEC due to the likelihood of fraud. This test compares the effect of city crime on fraud between two subsamples–low CEO compensation versus high CEO compensation. Control variables are as defined in Appendix A. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 7: Effect of City Crime on Fraudulent Financial Reporting – Geographical Proximity to the SEC

	Fraud	
	Sub-Sample Based on Geographical Proximity to the SEC	
	1st Quartile (Closer to SEC)	4th Quartile (Farther from SEC)
City Crime	11.3*	2.0
	(5.4)	(8.5)
Firm Size	-0.06	0.03
	(0.06)	(0.7)
Book-to-Market	0.09+	0.05
	(0.05)	(0.05)
Loss	-0.3	0.1
	(0.4)	(0.4)
Leverage	-0.2*	-0.09+
	(0.06)	(.06)
Constant	-5.3**	-5.6**
	(0.4)	(0.7)
Observations	12,587	7,850

Table presents results of a logistic regression, where the coefficients are log-odds ratios. The dependent variable is the categorical variable, *Fraud*, which is equal to 1 if a company receives AAERS from the SEC due to the likelihood of fraud. This test compares the effect of city crime on fraud between two subsamples–firm headquarters closer to the SEC versus firm headquarters farther from the SEC. Control variables are as defined in Appendix A. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Chapter Five: Conclusion

This dissertation offers a comprehensive exploration of the influence of external environmental factors on business outcomes, particularly focusing on the impact of social media responses (Chen, 2014; Green et al., 2019; Kuhnen & Niessen, 2012; Meadows & Meadows, 2016; Wu, 2004) and crime rates (Botrić, 2021; Hua & Yang, 2017; Motta, 2017) on firms' stock performance and reporting quality, respectively. Through the three-paper model of the dissertation, my findings have provided significant insights into understanding the dynamics between these external forces and their implications for businesses.

The first two chapters delve into social media communications, revealing the substantial influence of controversial tweets on stock market returns. The analysis reveals a nuanced relationship: while I find a significant negative relationship between the level of controversy in a small subset of controversial CEO tweets and stock market returns, controversial firm tweets, on the other hand turns out to be positively correlated with long-run stock market returns. To capture controversy in tweets sent by both firms and CEOs, I followed the concept of ratioed tweets – replies higher than retweet counts – as tweets get ratioed when the Twitterverse finds a tweet objectionable and controversial. The negative association between controversial CEO tweets and stock market returns can be explained by social media's *cancel culture*, which is the withdrawal of support from the users due to the posts being deemed "unacceptable" or highly problematic (Ng, 2020). The unexpected findings of a positive relationship between controversy and stock performance hint at a price-distorting behavior of social media (Jia et al., 2020) and the emotive nature of social media-driven stock trading by less-rational investor groups (Baker & Wurgler, 2007; Barber et al., 2009; Kumar & Lee, 2006).

Another significant finding of my research is that market generally reacts negatively when high retweet counts are examined in relation to controversial tweets. Moreover, sentiment analysis indicated that the interaction between controversial tweets and tweet sentiment is associated with positive and significant stock returns, which suggests that positively oriented controversial tweets exhibit the potential to counteract adverse stock price effects. My research on controversial tweets further explores the moderating effects of CEO stardom, high individual stock ownership, and earnings announcement news on the relationship between controversial tweets and market returns. These insights shed light on the importance of strategic social media disclosure by both firms and their CEOs.

Until now, the topic of controversial tweets concerning capital market consequences has not been explored. Consequently, my research findings offer a preliminary understating of the dynamics between controversy in firms' and CEOs' tweets and stock market returns. Research in this area can be further explored to determine the impact of controversial tweets on other business outcomes, such as sales, customer satisfaction, goodwill, CEO hire/fire, etc. and on the outcomes for the CEOs as well, namely, their compensation, reputation, and tenure.

The final chapter of this dissertation explores an unconventional yet crucial dimension– the correlation between city crime rate and firm-level accounting fraud. The findings indicate a positive relationship between higher city crime rates and an increased likelihood of committing accounting fraud among firms in these areas. Furthermore, my study identified a link between CEO compensation and a higher likelihood of accounting fraud in high-crime-rate cities, aligning with theories that tie managerial behavior to wealth maximization. Proximity to the SEC is another significant factor that influences how crime increases the likelihood of receiving AAERs by firms for fraud cases.

Accounting misconduct is a big area in accounting and finance research. Understanding the sensitivity of accounting behavior to local crime is crucial for businesses, city planners and policymakers. Future research can explore the change in headquarters' location and examine the effect of the shift on accounting misconduct or financial mis(reporting) in line with the "flight from blight" theory of Bradford et al. (1973). Future studies can also explore the impact of crime by categories of sex, age, income, education and other demographics on firm-level outputs. Executive-level criminal records can be further explored to see their impact on firm governance and internal control. Capital market studies can be designed around the AAER issue date, especially the variation of the market reaction to AAER events based on geographic crime differences.

In summary, my dissertation contributes to the growing research area examining how big-picture environmental factors affect businesses. By exploring how social media, crime rates, and business results are connected, this study lays a foundation for more academic research into this area.

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