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THE EFFECTS OF INFORMATION DISSEMINATION IN FINANCIAL MARKETS

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THE EFFECTS OF INFORMATION DISSEMINATION IN FINANCIAL MARKETS

SUMMARY

The research purpose of this doctoral dissertation is to analyze and evaluate the relationship between information dissemination in financial markets and specifically the impact on companies' stock returns. Information on its own is one of the architects of the stock market movements, which additionally plays an important part in the shaping up of the business environment. This triggers the idea of linking the media as an information dissemination source with financial markets and observing the causal-comparative relation between the two.

Observing the 2014-2016 Ebola disease outbreak events, Chapter 1 examines whether there is an impact from the Ebola outbreak events upon the U.S. financial markets. This chapter's goal is to analyze information dissemination and the importance of geographic proximity of the event to the investors as well as to the financial markets. The empirical analysis employs two sets of methodology. The event-study methodology is used to evaluate the economic impact of the events upon companies' stock returns. The cross-sectional analysis is used to analyze whether the geographic proximity between the events, investors, and financial markets play important role upon companies' returns, size of the companies, companies' industry of operation, investor sentiment, and whether the companies are exposed in the media. The results in Chapter 1 show that the information disseminated from the Ebola outbreak events negatively affects and is more relevant for companies that are closer in distance to both the birthplace of the Ebola outbreak events and the financial markets. Furthermore, the results show that the effect is larger for small and more volatile stocks, stocks belonging to a specific industry, and for the stocks exposed to the intense media coverage. Lastly, I observe that the implied volatility increases after the Ebola outbreak events; that is an indication of elevated perceived risk.

Chapter 2 aims at overcoming the problem of social media's credibility as an information dissemination source. In this chapter I evaluate President Trump's political power on the financial markets through his mass-media and social media statements around the 2016 U.S. presidential elections. I use hand collected data from Trump's Twitter archive and mass-media distributed newspaper articles from The New York Times, Chicago Tribune, and The Wall Street Journal. The empirical design consists of three sets of methodology. I use the logistic regression analysis to investigate factors driving the likelihood of a firm being mentioned by Trump during the 2016 U.S. elections. Event-study is used to evaluate the economic impact of Trump's statements on companies' returns. To further analyze the impact of Trump's statements I use the cross-sectional regression analysis. The results show that Trump is more

inclined towards mentioning in his public statements the companies to which he has an established business and political connections, companies present on the international markets as well as large companies in the sample. The analysis of the linguistic tone in Trump's statements rather suggest that negative statements result in depressed stock prices of the companies he publicly mentions. Lastly, I find that Trump's information dissemination affects companies' trading volume and stock price volatility.

Chapter 3 examines whether information disseminated from dramatic events, such as nuclear energy accidents, influences the U.S. financial markets. The data used in this chapter encounters information on all publicly available nuclear accidents in the period from 1944 to 2017 taking place in the U.S., Japan, and France. Consistent with the previous chapters, I use event-study and cross-sectional methodologies to perform the analysis. More specifically, Chapter 3 examines whether the geographic proximity of information disseminated by the nuclear accident events affect stock prices in the U.S. Next, it observes whether the events effect differ across company size and industry of operation, and whether the events influence stock price volatility to gauge whether the nuclear accident events trigger fear and anxiety among investors. I find that information disseminated from the nuclear accidents is more relevant for the companies that are geographically closer to both the birthplace of the accident and the financial markets. Furthermore, the results show that the effect is more pronounced for small cap stocks, stocks of specific industry, and by perceived risk surge; that is, the implied volatility increases after the nuclear accident events implying the presence of fear and anxiety around accident days.

Keywords: Business connections, Ebola outbreak**,** Event study, Geographic proximity, Information dissemination**,** Investor sentiment**,** Linguistic tone, Mass-media, Media coverage, Nuclear accidents, Political connections, Stock price reaction, Twitter

VPLIV ŠIRJENJA INFORMACIJ NA FINANČNE TRGE

POVZETEK

Raziskovalni namen te doktorske disertacije je analiza in ovrednotenje odnosa med širjenjem informacij v finančnih trgih in specifičnim vplivom na donosnost delnic podjetij. Informacije so same po sebi eden izmed oblikovalcev gibanja delniških trgov, ki poleg tega igrajo pomembno vlogo pri razvoju poslovnega okolja. To sproža idejo povezave med mediji kot razširjevalcem informacij in finančnimi trgi in posledično opazovanje vzročno-primerjalnega odnosa med njimi.

V 1. poglavju ugotavljam, ali so dogodki izbruha ebole leta 2016 vplivali na finančne trge ZDA. Cilj tega poglavja je analiza širjenja informacij in pomembnosti geografske bližine dogodka tako vlagateljem kakor tudi finančnim trgom. Empirična analiza se poslužuje dveh metodologij. Metodologijo študije dogodka uporabim za ovrednotenje vpliva dogodkov na donosnost delnic podjetij. Presečna analiza služi ugotavljanju, ali geografska bližina dogodkov, vlagateljev in finančnih trgov pomembno vpliva na donosnost, velikost in panogo poslovanja podjetja ter zaupanje vlagateljev in ali so ta podjetja izpostavljena v medijih. Ugotovitve 1. poglavja kažejo, da je širjenje informacij o dogodkih izbruha ebole negativno vplivalo na podjetja in je bilo relevantnejše za tista, ki so bližje tako izvoru izbruha ebola kot finančnim trgom. Poleg tega ugotovitve opisujejo večji učinek za manjše in bolj volatilne delnice, delnice podjetij specifične panoge ter delnice podjetij, ki so intenzivno medijsko pokrite. Nazadnje je iz ugotovitev mogoče razbrati, da se je implicitna volatilnost po izbruhu ebole povečala; to je kazalnik povišanja zaznanega tveganja.

V 2. poglavju obravnavam težavo verodostojnosti družbenih omrežij v vlogi vira širjenja informacij. V tem poglavju ovrednotim politično moč predsednika Trumpa nad finančnimi trgi z njegovimi izjavami v množičnih medijih in na družbenih omrežjih v času predsedniških volitev leta 2016 v ZDA. Uporabim ročno zbrane podatke s Trumpovega profila na Twitterju in časopisnih člankov množičnih medijev The New York Times, Chicago Tribune in The Wall Street Journal. Empirična zasnova sestoji iz treh metodologij. S pomočjo logistične regresijske analize raziščem dejavnike, ki vplivajo na verjetnost, da bi predsednik Trump omenil podjetje v času volitev leta 2016 v ZDA. Študijo dogodka uporabim za ovrednotenje ekonomskega vpliva Trumpovih izjav na donosnost podjetij. Da bi lahko dodatno analiziral vpliv Trumpovih izjav, uporabim presečno regresijsko analizo. Ugotovitve kažejo, da se Trump v svojih javnih izjavah nagiba k omembi tistih podjetij, s katerimi ima vzpostavljene poslovne in politične povezave, ki so prisotna na mednarodnih trgih in so velika. Analiza tona Trumpovih izjav kaže na to, da negativne izjave povzročajo padec cene delnic podjetja, katero javno omeni. Nazadnje ugotovim, da Trumpovo širjenje informacij vpliva na obseg poslovanja in volatilnost

cene delnic podjetja.

V 3. poglavju raziščem, ali širjenje informacij o dramatičnih dogodkih, kot so jedrske nesreče, vplivajo na finančne trga ZDA. V tem poglavju uporabljeni podatki vključujejo vse javno dostopne informacije o jedrskih nesrečah od leta 1944 do 2017, ki so se zgodile v ZDA, Franciji in na Japonskem. Kakor v poglavjih poprej uporabim študijo dogodka in presečne metodologije za izvedbo analize. Natančneje, v 3. poglavju ugotavljam, ali geografska bližina širjenja informacij o jedrskih nesrečah vpliva na cene delnic v ZDA. Nadalje raziskujem, ali se učinki teh dogodkov razlikujejo glede na velikost in panogo podjetja in ali ti dogodki vplivajo na volatilnost cene delnic, da bi ugotovil, če jedrske nesreče sprožajo strah in tesnobo pri vlagateljih. Širjene informacije o jedrskih nesrečah v analizi so relevantnejše za podjetja, ki so geografsko bližje tako izvoru nesreče kot finančnim trgom. Poleg tega ugotovitve kažejo, da je učinek izrazitejši pri delnicah z nizko kapitalizacijo, delnicah določenih panog in pri porasti zaznanega tveganja; to pomeni, da se implicitna volatilnost poveča po jedrski nesreči, kar kaže na strah in tesnobo v dneh po nesreči.

Ključne besede: poslovne povezave, izbruh ebole, študija dogodka, geografska bližina, širjenje informacij, zaupanje vlagateljev, jezikovni ton, množični mediji, medijska pokritost, jedrske nesreče, politične povezave, odziv cen delnic, Twitter

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INTRODUCTION

Background Motivation of the Dissertation

Economists have extensively argued that stock prices ameliorate capital allocation by aggregating dispersed information and pointing to the most promising investment opportunities. Even though several structural aspects of the relation between the stock market and the real economy have been examined, existing theories have not yet assembled all the links in the chain from the functioning of stock markets to the information dissemination. Businesses around the world are affected by the economic environment in which they operate. Any change in the business environment has a specific effect on firm behavior. Information, on its own, plays an important part in the shaping up of the business environment. The spontaneity of information and assimilation by the business entities, in any sort of business transactions, affects the business or the value of a business (D'Avolio, 2002). The transmission of the information to the business as an entity, is one of the structural architects of the stock market movements. How investors obtain information is another phenomenon of great importance to understanding financial markets (Edmans et al., 2007).

Considering that media are increasingly recorded as key sources of information dissemination in financial markets, the purpose of this doctoral dissertation is to analyze and evaluate the relationship between information dissemination and its impact on stock returns. Historically, this relationship has been subject of research to Klibanoff et al. (1998), Tetlock et al. (2008), Fang and Peress (2009), Boulland et al. (2016). For example, Klibanoff et al. (1998) who have been extensively working in this field, show how investors assign more importance to the news to which more attention has been given from the media, than to the news to which less importance has been assigned, even if the news has the same fundamental value. More specifically, Klibanoff et al. (1998) collect country-specific news reported on the New York Time's front page and they test investor misperception, where investors incorrectly perceive fundamental signals while predicting future fundamental signals. They find that some investors react more to the fundamentals after well-announced/publicized news, thus affecting the prices and relating them more to the given fundamentals' pattern.

Tetlock et al. (2008) who analyzes interactions between media's disseminated content and stock market returns has given another contribution to this research area. They construct a model of noise and linguistic content analysis according to DeLong et al. (1990a) and Campbell et al. (1993) and show that a high portion of media pessimism significantly predicts market price slumps. Furthermore, a valuable insight found is that high trading volume is associated with the uncommon low or high values of media pessimism. Lastly, it has been shown by Tetlock et al. (2008) that low market returns are related to high media gloominess.

Fang and Peress (2009) add up with a research work on the media's coverage and cross section of stock returns. They enlighten the power of the media on the financial markets by studying stock return premia for stocks with media and no media coverage. They show that on average, stocks not featured in the media gain 0.20% more per month than stocks that are covered more often. More recently, Engelberg and Parsons (2011) analyze the causal relation between stories reported by the media and stock market reactions too. The main difference between their research and that of Fang and Peress (2009) is that they measure media's effects on stock returns on a local level. They show that the local press coverage increases the trading volume of local investors for about 50%. Their results clearly show that media coverage does stimulate local trading activity and that geographic proximity matters because of the interests of the local investors for a certain security (see also Boulland et al., 2016).

A set of previous event studies provide an important economic rationale to motivate the dissertation story which evolves around investor reaction, and fear and short-run investment opportunities (see Kaplanski and Levy 2010a; Ferstl et al., 2012; Acemoglu et al., 2016). For example, Kaplanski and Levy (2010a) reveal that negative sentiment driven by fear, in particular, affects investment decisions. They examine the effect of aviation disasters on stock prices and find an average market loss of more than $60 billion per aviation disaster, whereas the estimated actual loss is no more than $1 billion following a price reversal two days after the disaster. Ferstl et al. (2012) investigate the impact of the nuclear disaster in Fukushima-Daiichi on the daily stock prices of French, German, Japanese, and U.S. nuclear and alternative energy firms as well as roughly estimate the total cost for the economy from the disaster. On the first day after the disaster, the S&P Global Nuclear Energy index declines -7.71%, whereas the index reverses on the second day to -5.35%; roughly estimating a total cost from the disaster of $187 billion. Acemoglu et al. (2016) suggests that at least in the minds of investors, unexpected events that impose short term fear in the markets are of specific interest among the financial market investors due to the opportunity to engage in action in the short time between the event day and the expected stock price reverse moment.

Giving the significant previous research insights on the relationship of the media as a source of dissemination of information and the financial markets, this dissertation contributes with filling up the missing parts in the literature primarily from three perspectives:

1) by studying a stock price reaction to the geographic proximity of information to the financial markets;
2) by studying the role of political figures acting as a credible source of information dissemination and their impact on the financial markets' behavior;

3) by studying the financial markets reaction, investor sentiment, fear and short run investment opportunities, and industry effects to dramatic events such as nuclear energy accidents and Ebola disease outbreak.

Research Questions Addressed in the Dissertation

Chapter 1 of the dissertation looks at the realm of behavioral finance to investigate the impact of geographic proximity of information on the U.S. companies' stock prices as an aftermath of the 2014-2016 Ebola outbreak events. Motivated by previous studies, mainly Kaplanski and Levy (2010a, 2010b) and Engelberg and Parsons (2011), that examine securities' reaction to certain events as well as securities' reaction as a result of the distance between an event and the investors, in this chapter I develop the idea to interrelate the 2014-2016 Ebola outbreak events - as a source of information dissemination, the media – as an information distributor, the location of the Ebola events – as a geographic location, and the financial markets – as a respondent to the Ebola events. To evaluate the impact upon companies' stock prices the following research questions are addressed in this chapter:

Research question 1.1: Does the geographic proximity of information (disseminated by the Ebola outbreak events) have a statistically significant impact on the financial markets?

I collect data on the 2014-2016 Ebola outbreak events that take place on U.S. soil, West African Countries (WAC) region, and Europe, and predict that the event effect (on the day of the event) will be the strongest for the U.S. companies that are geographically closer to the event location and to the financial markets. In the second part of the analysis the following question is addressed:

Research question 1.2: Is the event effect stronger for the stock returns of small companies relative to large companies?

For this part, the U.S. companies are categorized in 10 deciles where in decile 1 are the large companies and decile 10 represents the set of small companies. Previous research suggests that small companies are usually the ones that are affected the most by events such as disasters (Edmans et al., 2007). Following the idea from question 1.2, in the third part of the empirical analysis the following research question is addressed:

Research question 1.3: Is the effect on the event day (i.e., day 0) larger for more volatile stocks than for less volatile stocks?

The expectations go alongside Kaplanski and Levy (2010a), which suggest that the event effect is expected to be larger for more volatile stocks, which are usually the small stocks, than for less volatile stocks. Next, the Ebola outbreak event effects are investigated across the U.S. industries, thus the following question is addressed:

Research question 1.4: How (positively or negatively) the Ebola outbreak events affect each U.S. industry?

Initial predictions suggest that some industries, like healthcare or hazmat equipment producers, would benefit from the Ebola events and other industries would be negatively affected. Lastly in the empirical analysis the following research question is addressed:

Research question 1.5: Are the companies exposed to intense media coverage more affected by the Ebola outbreak events than the companies receiving less media exposure?

Following Fang and Peress (2009), predictions suggest that securities exposed to intense media coverage would be more affected by the Ebola events than the securities receiving less media coverage.

In Chapter 1, the empirical design consists of two sets of methodology. The event study methodology observes the economic impact of the Ebola outbreak events upon companies' stock prices through the one-factor and two-factor market model. The cross-sectional analysis further examines the impact of the events across the size of the companies, companies' industry of operation, intensity of media coverage and investor sentiment.

Chapter 2 of this dissertation investigates the impact of social media and political power on the U.S. financial markets. The central figure in this chapter is President Donald J. Trump and his public statements about specific companies. Previous research shows that the stock market is sensitive to political news where even political figures who may not yet be in power can influence stock returns and trading volume (Julio and Yook, 2012). Chapter 2 addresses the following research questions:

Research question 2.1: What are the factors describing the likelihood of a firm being mentioned by Trump in the period from June 2015 to June 2017?

Research question 2.2: Does the linguistic tone used in Trump's statements predict stock market returns, affects the trading volume, and the stock price volatility?

Research question 2.3: Are the political factors such as donations to certain party and business connection of a company to the presidential candidate likely to influence the stocks of the company?

Chapter 2 encompasses data on Trump's tweets and media statements to estimate a logistic regression to uncover the factors driving the likelihood of a firm being mention by Trump around the 2016 U.S. elections. The linguistic tone of the statements, political orientation of the companies as well as the political and business connections between Trump and the companies are further added to the event study and cross-sectional analysis to examine the interrelations between social media, political power, and the financial markets in the U.S.

Chapter 3 evolves around the investigation of nuclear accidents occurring from 1944 to 2017 and their impact on the U.S. publicly listed companies. Motivated from dramatic nuclear disasters, such as that of the Fukushima Daiichi nuclear plant in March 2011, Chapter 3 addresses the following research questions:

Research question 3.1: Does the geographic proximity of information have a statistically significant impact on the financial markets, observing the stock returns of the U.S. publicly listed companies as a result to the nuclear events that took place in the U.S., France, and Japan?

Research question 3.2: Is the event effect stronger for the stock returns of small companies relative to large companies?

Research question 3.3: Do the nuclear accident events affect the implied volatility on the day of the accident?

Research question 3.4: How (positively or negatively) the nuclear accidents affect each industry?

Research question 3.5 Is there influence of the accidents that channels through the fear channel and triggers fear and bad mood among the investors, which further contributes to depressed stock prices?

Previous studies in the existing literature that focus on the consequences of nuclear accidents find negative daily abnormal returns for all firms in the nuclear energy sector (Bowen et al., 1983; Kalra et al., 1993). Chapter 3 involves data on all documented and publicly available nuclear accidents from 1944 to 2017 from the U.S. Department of Defense. This chapter addresses the above listed research questions through the event study and cross-sectional analysis to observe the impact of the nuclear accident events on stock returns, and to further examine the impact across company size, industry of operation, and investor sentiment.

Structure and Contents of the Dissertation

The core structure of this doctoral dissertation consists of three chapters. All three chapters are based on observations and evaluations of the U.S. financial markets. The first chapter starts by introducing how events such as the 2014-2016 Ebola outbreak affects investor sentiment, investor's willingness to participate in the financial markets during turbulent times, and what could be the potential role of the geographic proximity of the information to the investors and to the financial markets. Section 1.3 presents thorough theoretical background and synchronizes the main idea of the first chapter to the past literature in order to find and fill the gaps in this niche of studies. Section 1.4 presents the data examined in the first chapter which mainly consists of the Ebola outbreak events on U.S. soil, in the West African Countries (WAC) region and in Europe. Section 1.5 presents the one and two factor market models from the event study methodology as well as a cross-sectional analysis model. In addition, this section also lists all the hypotheses tested in this chapter. In section 1.6 the results are presented in seven sub-categories. I start with presentation and discussion of the event study results, then I present the results on the geographic proximity of information to the financial markets, next I analyse whether the proximity of information differs among stocks of different size, stocks belonging to certain industry, and stocks categorized by their price volatility. I end this section presenting results on the intensity of media coverage of certain stocks. Lastly, section 1.7 concludes the chapter.

The second chapter starts by introducing the role and problems of the social media as an information dissemination source used by people with public influence. It further presents the main goals and problems to be tackled in this chapter, and later summarizes the results and contributions of the study. Section 2.3 presents theoretical background as well as where this chapter fits in the literature. Section 2.4 thoroughly explains the data, data sources, and methods of collecting the data. Section 2.5 presents the three sets of methodology, i.e. logistic regression analysis, event study, and cross-sectional analysis; as well as it lists the hypotheses tested in this chapter. Sections 2.6 and 2.7 present the results. Section 2.8 show the results from a detailed robustness tests analysis, and lastly, section 2.9 concludes the chapter.

Chapter 3 opens with short overview of historical events of nuclear energy accidents and their impact on the economy. Section 3.3 provides theoretical background of this chapter and describes how events such as nuclear accidents affect the whole business and economic environment. Section 3.4 describes the data, i.e. the nuclear energy accidents from 1944 to 2017, and the methods of collection of the data. Section 3.5 presents the methodology as well as the hypotheses tested. In section 3.6 I present the results which are divided in seven sub-sections. I start this sub-section with the event study results and continue to the results obtained from the cross-sectional analyses. Lastly, section 3.7 concludes the chapter.

The fourth chapter serves as a general discussion and starts by summarizing the main findings of the dissertation. The summary is followed by the scientific, methodological, and theoretical contributions of the dissertation.

1 STOCK PRICES AND GEOGRAPHIC PROXIMITY OF INFORMATION: EVIDENCE FROM THE EBOLA OUTBREAK[♣]

1.1 Overview

Behavioral finance studies reveal that investor sentiment affects investment decisions and may therefore affect stock pricing. This chapter examines whether the geographic proximity of information disseminated by the 2014–2016 Ebola outbreak events combined with intense media coverage affected stock prices in the U.S. I find that the Ebola outbreak event effect is the strongest for the stocks of companies with exposure of their operations to the West African countries (WAC) and the U.S., and for the events located in the WAC and the U.S. This result suggests that the information about Ebola outbreak events is more relevant for companies that are geographically closer to both the birthplace of the Ebola outbreak events and the financial markets. The results also show that the effect is more pronounced for small and more volatile stocks, stocks of specific industry, and for the stocks exposed to the intense media coverage. The event effect is also followed by the elevated perceived risk; that is, the implied volatility increases after the Ebola outbreak events.

1.2 Introduction

One of the central issues in the behavioral finance literature is to explain why some market participants make seemingly irrational decisions. A relatively large number of studies show that "bad mood" and anxiety may affect investor sentiment. Anxiety drives investor sentiment against taking risks, contributes to pessimism regarding future returns and thus dictates asset price movements (see for e.g. Baker and Wurgler, 2007; Cen and Liyan-Yang, 2013; Lucey and Dowling, 2005).

Early studies observe, for instance, that the weather, which is a well-known driver of peoples' mood, tends to positively commove with daily stock returns (Hirshleifer and Shumway, 2003). In more recent studies, Kaplanski and Levy (2010a, 2010b) study the impact of sporting games and aviation disasters on investor sentiment. They find that aviation disasters negatively affect investor sentiment and temporarily increase the fear for trading. Donadelli et al. (2016a) analyze whether investor sentiment, measured by results of the FIFA World Cup, is related to the U.S. sectoral stock returns. They find some support that sport sentiment is priced in the financial

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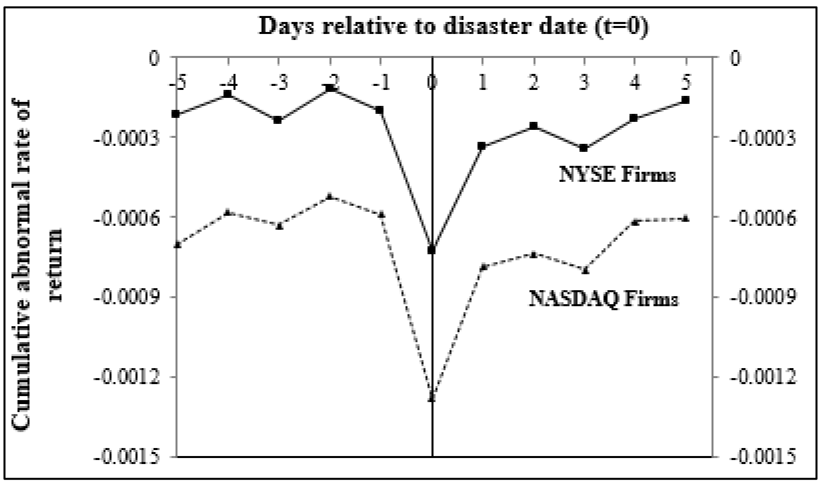
[♣] This chapter is co-authored with Matej Marinč. The authors would like to thank Aleksandar Šević, Aljoša Valentinčič, Igor Lončarski, Nuria Alemany, Vasja Rant and the participants at the 15th INFINITI Conference on International Finance in Valencia, Spain for their valuable comments and suggestions. This chapter has been published in *International Review of Financial Analysis, ISSN 1057-5219. [Print ed.], [in press] 2017, doi: 10.1016/j.irfa.2017.12.004*.

sector but not in other sectors. Yuen and Lee (2003) study risk-taking tendencies in various mood states. They show that people in a depressed mood have lower willingness to engage themselves in risky situations than people in positive or neutral mood states.
I focus on the 2014–2016 Ebola pandemic outbreak and I analyze its outbreak events based on World Health Organization (WHO)'s alerts and mass-media news on pandemic diseases to examine the effect on companies' stock returns.

As a preliminary exploration, I plot cumulative abnormal returns surrounding the Ebola outbreak event days in Figure 1.1. I find negative cumulative abnormal returns on the event day and a reversal effect one day after the event. Possible reason for this effect may be that investors act irrationally to the news on the Ebola outbreak and after one day they stabilize their behavior.

Figure 1.1 Cumulative Abnormal Rate of Return (CAR)



Notes. The figure depicts the Ebola outbreak effect surrounding the event day (t=0) proxied by the CARs calculated using the market model for my sample of companies listed on the NYSE Composite and NASDAQ Composite. The events occurred during the 2014–2016 Ebola outbreak period (3-year period) and include a total number of 103 event days of the disease outbreak. The effect presented in the figure is based on a preliminary evaluation and it does not account for overlapping among the events' windows.

I begin the analysis by examining whether the geographic proximity of the information (disseminated by the Ebola outbreak events) to the financial markets has statistically significant impact on the U.S. stock prices. Motivated by Francis et al. (2007) and Engelberg and Parsons (2011), I anticipate that the Ebola outbreak events unequally affect investors' mood—their sentiment about stock returns—depending on investors' distance to the Ebola events from the markets. I classify the U.S. publicly listed companies into three groups depending on whether their operations have exposure to the U.S. only, the West African countries (WAC)[1], and Europe. I also distinguish among the Ebola outbreak events depending on where they occur (i.e., in the

[1] WAC region: Liberia, Guinea, Sierra Leone, Nigeria, Mali, and Senegal.

U.S., the WAC or Europe). I find that the Ebola outbreak event effect is the strongest for the stocks of companies with exposure of their operations to the WAC and the U.S. for the events located in the WAC and the U.S. This result suggests that the information about Ebola outbreak events is more relevant for companies that are geographically closer to both the birthplace of the Ebola outbreak events and the financial markets.

Second, I investigate whether there is a difference in the magnitude of the effect in portfolios classified by capitalization size. I find that the negative effect of the Ebola outbreak events is more pronounced for small companies relative to large companies. A potential explanation for this effect is that information dissemination is less effective for small cap stocks compared to large cap stocks.

Next, I examine whether the Ebola outbreak events affect investor sentiment proxied by the implied volatility. The results show that implied volatility increases following the Ebola outbreak event days but then subsides—indicating a mood-driven effect. In addition, I also build portfolios of securities sorted by volatility. The impact of the Ebola outbreak events on abnormal stock returns is negative and the most pronounced for small, illiquid, and more volatile stocks. For large, liquid, and less volatile stocks, the effect is also negative but of smaller magnitude.

Lastly, I evaluate the magnitude of the effect from the Ebola outbreak events for securities highly exposed in the media and securities belonging to a specific industry. I find evidence that the event effect is stronger for the securities exposed to the intense media coverage than for the securities receiving less media exposure. The event effect is also strong for securities belonging to the Healthcare equipment, Pharmaceutical, and Aviation industry.

This study makes the following contributions. With an important exception of Donadelli et al. (2016b) who analyze various globally dangerous diseases and examine their impact upon pharmaceutical companies' stock returns, this study is fully focused on the impact of the Ebola outbreak events on the financial markets with the intent to analyze information dissemination and the importance of proximity of the event. Relating to the strand of literature that examines the effect of investor sentiment on the financial markets, this chapter is closely related to Yuen and Lee (2003), Kaplanski and Levy (2010a, 2010b), Cen and Liyan-Yang (2013), and Donadelli et al. (2016a) and shed new light on the role of geographic proximity of information to the financial markets and its psychological effects on investors' decision making process. My results show evidence that there is a clear relation between the relevancy of the Ebola outbreak events to investors' actions and the magnitude of the event effect.

I contribute to the literature observing the effects of media coverage on investor sentiment, by considering the geographic proximity of the information to the financial markets. My findings relate to Klibanoff et al. (1998), Fang and Peress (2009), Engelberg and Parsons (2011), Peress (2014), and Donadelli (2015) who find that investors react more to media covered events and pay more attention to stocks and news/events that are closer in distance to them.

This chapter is organized as follows. Section 1.3 provides a theoretical background. Section 1.4 describes the data. Section 1.5 reveals the methodology and delineates the hypotheses tested in this chapter. Section 1.6 presents the results. Section 1.7 concludes the chapter.

1.3 Theoretical Background

The main hypothesis of this chapter asserts that the geographic proximity increases the impact of the information related to the 2014–2016 Ebola outbreak on the financial markets. This hypothesis relies on the observed relations between: companies' exposure to different geographic regions of operation, companies' size and type of industry in which they operate, the media coverage of disease outbreak, the fear, and anxiety that Ebola outbreak provokes, and investors' risk aversion to invest when fear and anxiety increase.

Several studies observe the relationship between investors' mood, anxiety, and asset pricing (De Long et al., 1990; Cen and Liyan-Yang, 2013). My study is related to Kaplanski and Levy (2012) who observe the impact of negative events on holidays' sentiment effect in the financial markets. They find positive and significant holiday sentiment effect and significant and negative war sentiment effect, which overtakes the positive holiday sentiment effect. Kamstra et al. (2003) study the impact of sunshine on asset prices. They find that due to seasonal characteristics, the return on the assets is lower when the daylight period is shorter.

My study is also related to Kaplanski and Levy (2010a, 2010b), who study the impact of sporting games and aviation disasters on investor sentiment. They show that aviation disasters negatively affect investor sentiment and increase the fear for trading few days after the event. Alongside, several studies that analyze investors' trading behavior and attitude towards risk taking confirm the fact that fear, anxiety, and depression are positively related to investors' risk aversion (see, Mehra and Sah, 2002; Hanock, 2002).

Moreover, Yuen, and Lee (2003) study risk-taking tendencies in various mood states. Their results show that people in a depressed mood have lower willingness to engage in risky situations than people in positive or neutral mood states. Donadelli et al. (2016b) examine whether investor mood driven by various dangerous diseases is priced in pharmaceutical companies' stocks. They argue that global diseases should not trigger rational trading and they find positive effect upon pharmaceutical companies' stocks.

I focus on the 2014–2016 Ebola outbreak—a major disease outbreak, which was regarded as a public health emergency of international concern (PHEIC) by the WHO—to examine its impact on companies' stock returns. My study contributes to this strand of literature by joining investor sentiment and the information flow from the geographically dispersed Ebola disease events. It adds up to the literature by examining investors' willingness to invest under the Ebola saturated state of mood. Finally, it observes investors' preference for investing in stocks of certain capitalization size and industry of operation.

Another set of studies identifies a relationship between the media as an information disseminator and investor sentiment. Blendon et al. (2004) study the intensity of media coverage of the Severe Acute Respiratory Syndrome (SARS) disease outbreak. They find that the media tends to disproportionately cover rare events, new events, and dramatic events—the ones that kill many people at once. Hence, as shown by Kepplinger and Hans Mathias (2008), when an unusual event occurs, the media starts hunting "newer" news on the same specific topic.

Klibanoff et al. (1998) show that investors assign more importance to news to which more attention has been given by the media than to news to which less importance has been assigned even if the news items have the same fundamental value. More specifically, Klibanoff et al. (1998) collect country-specific news reported on the New York Times front page and test investors' misperceptions, where investors incorrectly perceive the signals while predicting future fundamental security price behavior. The study finds that some investors react more to the fundamentals after well announced/publicized news thus affecting prices directly (see also Peress, 2008 and Mairal, 2011).

Fang and Peress (2009) conduct research on media coverage and a cross-section of stock returns. They highlight the impact of the media on financial markets by studying return premiums on stocks for stocks with a media coverage versus stocks without a media coverage. Fang and Peress (2009) find that, on average, stocks not featured in the media gain 0.20% more per month than stocks that are covered more often.

Peress (2014) investigates the causal impact of the media on trading and price formation by observing newspaper strikes in several countries. He finds that, on strike days, trading volume falls by 12%, the dispersion of the stock returns and returns' intraday volatility is reduced by 7% whereas the aggregate returns show no signals. Donadelli (2015) measures policy-related uncertainty based on the volume of Google searches. He finds that a Google-searched-based uncertainty shock has sizable adverse effects on the U.S. macroeconomic conditions and it negatively affects the industrial production, equity prices, consumer sentiment, and consumer credit.

Several other studies observe the impact of a media coverage on specific industries. Huberman and Regev (2001) perform a case study to observe the financial market effects of a media coverage of a major breakthrough in cancer research. Interestingly, the bio-pharmaceutical companies in their sample responded significantly stronger to the breakthrough after enthusiastic public attention triggered by a Sunday New York Times article even though the main findings have already been reported five months earlier.

My study is related to Francis et al. (2007) and Engelberg and Parsons (2011) who examine the role of a geographic location on an investor behavior and a firm decision-making process. Francis et al. (2007) find that a geographic proximity affects the dissemination of information. Geographically remote firms (usually rural firms) exhibit higher costs of debt than the firms located in the urban areas. To identify the role of a geographic proximity, Engelberg and Parsons (2011) measure media effects on stock returns at a local level. Their study finds that a local press coverage increases the trading volume of local investors up to 50%. Their results show that the media stimulates a local trading activity and that a geographic proximity matters. Differently than Engelberg and Parsons (2011), I examine the media coverage of global events having impact on companies exposed to different continental (geographic) locations of operations. In addition to the media coverage, I emphasize the role of trading intensity, stock variability, and liquidity.

1.4 Data

1.4.1 Ebola Outbreak Official Announcements

The data examined cover the entire history of mass-media circulated Ebola outbreak events considered as public health emergency of international concern (PHEIC) by the WHO, in the period from January 2014 to June 2016. The entire period incorporates 103 events taking place on the U.S. territory (31 events), in Europe (20 events), and on the WAC territory (52 events). I divide the events in two categories: "WHO reports" and "U.S. Newspapers Ebola Outbreak News". Events considered to be WHO reports are obtained from the official WHO website.[2] The events considered as U.S. Newspapers Ebola Outbreak News are obtained from the LexisNexis article search engine. To retrieve the Ebola outbreak news from the LexisNexis, the search term "2014 Ebola outbreak" has been used. In addition, I set the engine to browse the three largest U.S. newspapers by circulation reporting on the events and companies of interest.[3] About 51% of the news-events are published in The New York Times and the rest in The Washington Post and The Wall Street Journal.

[2] http://who.int/mediacentre/news/statements/en

[3] Printed and online subscription coverage on a national level is considered. http://www.cision.com/us/2014/06/top-10-us-daily-newspapers/.

The WHO reports that I encounter are official statements communicated to the public with regard to any new information related to the 2014–2016 Ebola outbreak. For example, on October 8, 2014, the first death case on the U.S. soil was publicly reported by the WHO.[4] In addition, the WHO emergency committee stated the conditions and security guidelines for disease prevention. Usually, the mass media uses such WHO reports releases to communicate the information to the broader public.

The U.S. Newspapers Ebola Outbreak News are to some extent daily or weekly updates on the current situation and include, for example, news about the number of infected or dead people per day or cross-border transmissions of the disease. I consider the fact that regularly spaced updates may be anticipated by the financial investors and thus priced preceding the actual update. For this reason, the sample of announcements considers only those updates documenting a news-event for the first time (e.g., the first-time cross-border transmission, the first-time announcement of a death case in the U.S.). Such a strategy helps ensure the independence of subsequent as well as sequential announcements.

Under the U.S. Newspapers Ebola Outbreak News, I also include release dates of official statements provided by the government institutions of publicly traded companies to avoid a missing event-information bias. For instance, information disseminated in the media about a particular company's actions against the Ebola outbreak (e.g., a vaccine development approval by the government institutions) may positively affect that company as well as its competitors' stock prices. All announcements are categorized and summarized in Table A.2.

1.4.2 Stock Market Data

To test whether the geographic proximity of information to the financial markets has an impact on companies' stock returns, I employ the value-weighted[5] total rates of return (see Table A.1 for definition) from the Center for Research in Security Prices (CRSP) of the New York Stock Exchange (NYSE) and NASDAQ Composite listed companies. In addition, I use the S&P500 index as a market performance benchmark. The NYSE Composite primarily contains large stocks generally characterized by good information dissemination whereas the NASDAQ Composite primarily includes some of the major tech stocks. Both markets were chosen for two reasons. First, they are the most closely followed in the world, thus very efficient with respect to dissemination of new information (Kaplanski and Levy, 2010a, 2010b). Second, the U.S. stock

[4] WHO: Ebola response Roadmap Situation Report. http://apps.who.int/
[5] Calculated from the stock market index whose elements are weighted in reference to the market value of companies' outstanding shares.

markets are among the leading stock markets in the world and account for almost 50% of the global market (Hou et al., 2011).

To fully capture the impact of geographic proximity, I further use Bloomberg's and Bureau Van Dijk's "Orbis" databases to build the portfolios of companies which are listed on the U.S. stock markets (NYSE and NASDAQ) and have exposure towards the regions of interest that correspond to the Ebola outbreak events' locations. I distinguish between exposures towards three different geographic regions: the U.S. only, the West African countries (WAC) region, and Europe. To ensure unbiased selection and categorization of the companies for each portfolio, I use the following four-step procedure.[6] First, I select the companies by status: I am interested in active and publicly listed companies. Second, I further select the companies that have a domicile in the U.S. Third, I match each company according to its operation ownership[7] with the specific country or region of operation (i.e., towards its exposure to the U.S., the WAC, and Europe[8]). Fourth, I set up the period of operation of the companies from January 2014 to June 2016. At the end, the sample consists of all companies listed on the NYSE and NASDAQ Composite, from which 1040 are classified as having exposure towards the U.S. only, 89 are classified as also having exposure towards the WAC region, and 309 towards Europe. Table A.3 and Table A.4 summarize the companies filtered by this procedure.

To further analyze a potential differential effect regarding the company industry, company size, and stock volatility, I employ Fama and French's (1993) 10 value-weighted portfolios constructed by size and volatility, obtained from the CRSP. The industry-based portfolio is created by selecting the 12 largest industries by contribution to the U.S. GDP in the period from January 2014 to June 2016. Industry data is acquired from the S&P Dow Jones Industry Index.

To measure investor sentiment, I employ the Chicago Board of Options Exchange's VIX and VXO[9] indices which serve as proxies for investor sentiment (see Whaley, 2009).

To observe whether the intensity of a media coverage has a significant impact on specific companies, from the event category U.S. Newspapers Ebola Outbreak News, I build a subsample of events (or in this case, newspaper articles) which I consider as heavily covered in the media. To do this as well as to match each event with the corresponding stock or company, I refer to the LexisNexis's database for global news and business information. I use the number as well as the frequency of newspaper articles published about that stock in the media. I employ the

[6]The four-step selection procedure is an automated filter available in both Bloomberg and Orbis databases software.
[7]Operation ownership: the company needs to have min 50.01% of known shareholders in the country of domicile and at least one subsidiary, affiliate or branch located in the region of interest. Source: Orbis.bvdinfo.com.
[8] Note that when matching the companies to the WAC region and Europe, I match each company with each country as a separate unit of the region.
[9] Retrieved from the Chicago Board of Options Exchange (CBOE) website: www.cboe.com.

LexisNexis "relevance score" to measure the quality of matching of an article to a specific company or stock. I use LexisNexis frequency of publishing score of 70% or above as a threshold to distinguish between the stocks with the intensive media coverage from the stocks without the intense media coverage. Lastly, the trading volume data (i.e., the proxy for trading intensity) and the price range and bid-ask spread (i.e., the proxies for stock market variability and liquidity) during the intense media coverage is obtained from the CRSP.

1.5 Methodology and Hypotheses

I employ an event-study and regression-based methodology to evaluate the impact of the 2014–2016 Ebola outbreak events on stock returns and to test the role of the geographic proximity of information.

The traditional event-study methodology is exercised to evaluate the general impact of the Ebola outbreak events upon companies' stock returns through the one-factor and two-factor market models, as inspired by prior research (e.g., Donadelli et al., 2016; Peress, 2014; Fang and Peress, 2009). The one-factor model is estimated as:

$$r_{i,t} = \alpha_0 + \beta_1 r_{m,t} + \varepsilon_t \quad (1)$$

where $r_{i,t}$ is the rate of return on stock i in period t and $r_{m,t}$ is the S&P500 rate of return, which serves as proxy for the market portfolio. The two-factor market model is estimated as:

$$r_{i,t} = \alpha_0 + \beta_1 r_{m,t} + \beta_2 r_{ind,t} + \varepsilon_t \quad (2)$$

where $r_{i,t}$ is the rate return on stock i in period t, $r_{m,t}$ is the S&P500 rate of return and $r_{ind,t}$ is the industry specific rate of return.

I begin the analysis by computing the cumulative abnormal returns (CARs) around the events considered. The abnormal returns (ARs) are defined as the difference between the actual rate of return of the stock considered and its ex-post expected rate of return over the whole length of the event window. I position 100 days in the estimation window and 11 days in the event window—5 days prior and 5 days after the event day noted as day 0 (I also repeat the calculation with [-5,+5], [0,+1] and [0,+5] event windows; for more on event study designs, see MacKinlay, 1997).

The sample of events that I observe is temporally clustered. Hence, the event study would suffer from overlapping windows if all events were considered. For this reason, I use only events with non-overlapping event windows (there is 40 such events). I use one of the two selection criteria to select events.

The first selection criterion is labelled as *the last occurrence* and chooses an event only if it is not followed by another event within 10 days after its occurrence. The second selection criterion is labelled as *the first occurrence* and selects events in chronological order (sequence). It starts with the first event in the sample, ignores all events showing up in the following 10 days, takes the next event in succession, ignores the following 10 days, and so on until the whole sample is exhausted. In a more illustrative way, assume there are five events taking place on dates $ɗ_0$, $ɗ_1$, $ɗ_2$, $ɗ_3$, and $ɗ_4$ where $ɗ_1$, $ɗ_2$, and $ɗ_3$ are temporally clustered. *The last occurrence* uses events for CAR calculation taking place on days $ɗ_0$, $ɗ_3$, and $ɗ_4$ and the *first occurrence* chooses $ɗ_0$, $ɗ_1$, and $ɗ_4$. With this strategy, I avoid unintentional bunching of events with overlapping windows in the same basket.

To observe whether the geographic proximity of information to the financial markets significantly affects stock returns, I run the following regression model (see, e.g., Kaplanski and Levy, 2010a, 2010b; Kamstra, Kramer, and Levi, 2003; Brown and Warner, 1985):

$$r_{i,t} = \gamma_0 + \sum_{j=1}^{5} \gamma_{1,j} r_{i,t-j} + \sum_{k=1}^{4} \gamma_{2,k} WD_{k,t} + \gamma_3 Tax_t + \sum_{l=1}^{3} \gamma_{4,l} EL_{l,t} + \epsilon_t \quad (3)$$

where $r_{i,t}$ is the rate of return of stock i on day t, γ_0 is the regression intercept, $r_{i,t-j}$ is the lagged dependent variable—the jth previous day rate of return, $WD_{k,t}$ with $k = 1, \dots, 4$ are dummy variables for the day of the week (Monday, Tuesday, Wednesday, and Thursday), Tax_t is a dummy variable for the first five days of the taxation year, and finally, $EL_{l,t}$ with $l = 1, 2,$ and 3, are dummy variables that denote the location where the event happened and equal 1 on the event day if the event happened in a specific region (either in the U.S., the WAC region, or Europe), and zero otherwise.

The reason for including rates of return in previous days, $r_{i,t-j}$ in the regression in (3) is a potential presence of a serial correlation. A serial correlation is one of the known anomalies that may contaminate the results and may occur as a result of time-varying expected returns, non-synchronous trading, or transaction costs (see, e.g., Schwert 1990a, 1990b, 2003; Campbell et al., 1993). I look at as many previous days' returns as is necessary to ensure that all significant correlations have been accounted for. In my case, it is the rates of return of the first five previous days. Following French (1980), Schwert (1990a), and Cho, Linton, and Whang (2007), I also acknowledge that the Ebola outbreak events may not be evenly distributed over the week either by the coincidence or by the nature of the events. I use dummies for each day of the week, WD_{it}, to capture the so-called "Monday effects" or "weekend effect."[10] Lastly, I add a dummy for the

[10] The "Monday" or "weekend effects" theory states that returns on the stock market on Monday will follow the trend from the previous Friday. For more evidence on the effect, see Cho, Linton, and Whang (2007).

first five days of the taxation year, Tax_t, starting at January 1, to account for the so-called "turn-of-the-year effect" (see, e.g., Chien and Chen, 2008).[11]

To account for a potential reversal effect (driven by positive/negative sentiments), I also run the following regression:

$$r_{i,t} = \gamma_0 + \sum_{j=1}^{5} \gamma_{1,i} r_{i,t-j} + \sum_{k=1}^{4} \gamma_{2,k} WD_{k,t} + \gamma_3 Tax_t + \sum_{l=0}^{5} \gamma_{4,l} E_{l,t} + \epsilon_t \quad (4)$$

where I look at the rate of return on the event day, $E_{0,t}$, and the first five subsequent trading days, $E_{l,t} (l = 1 \dots 5)$[12] (MacKinlay, 1997).

The following five hypotheses are tested in this chapter. First, I test whether the geographic proximity of information (disseminated by the Ebola outbreak events) has a statistically significant impact on the financial markets (more specifically, on companies' stock returns). I observe the U.S. publicly listed companies having exposure to events of three different geographic locations: the U.S. only, the WAC region, and Europe. I predict that the event effect (on the event day, i.e., day 0) will be strongest for the companies having exposure to the U.S. only and the WAC region since these companies are geographically closer to both the birthplace of the disease and to the financial markets (Engelberg and Parsons, 2011).

Second, I hypothesize that the event effect is stronger for the stock returns of small companies relative to large companies. This hypothesis is supported by the past research suggesting that local investors are usually the ones investing in small firms, thus their sentiment is affected by event information that is specific to the place and firm that they invest into (see, Brown and Cliff, 2005; Edmans et al., 2007).

Third, the Ebola outbreak as a type of event is perceived to increase bad mood as well as anxiety among investors, negatively affecting company returns. I proxy investor sentiment through stock price volatility. I hypothesize that the effect on the event day (i.e., day 0) is larger for more volatile stocks than for less volatile stocks (see, Kaplanski and Levy, 2010a).

Fourth, investors often hold very polarized stock portfolios. In my case, this means that some investors bet on positive impact of the Ebola outbreak on certain stocks while others hold the opposite view. Having this in mind, I select the 12 largest industries, by contribution to the U.S. GDP, and test how (positively or negatively) the Ebola outbreak events affect each industry. I

[11] "The "turn-of-the-year effect" follows a pattern of a unique trading volume and higher stock prices in the last week of December and the first two weeks of January (see, e.g., Chien and Chen, 2008).
[12] MacKinlay (1997) concludes that, as long as the event windows among the selected events are not overlapping, there is no strict rule about the size of the event window, hence symmetrical distribution of the days surrounding the main event day would imply simpler and faster computation.

anticipate companies from the pharmaceutical and biotechnological industry to be positively affected whereas the companies from aviation and tourism sectors to experience a negative impact.

Fifth, previous studies confirm that the intense media coverage significantly affects stock returns, trading volume, stock liquidity, and stock variability (see, Fang and Peress, 2009). I hypothesize that the companies exposed to the intense media coverage are more affected by the Ebola outbreak events than the companies that receive less media exposure.

1.6 Results

1.6.1 Event Study Methodology

I now present the results of the event-study methodology. Figure 1.2a-1.2f depict the CARs around the event date whereas Table A.5-A.9.1 in the appendix A reveal the event study results in greater details.

Figure 1.2a and Panel 1 of Table A.9.1 show that the one-factor market model CARs on the event day are statistically significant and negative for all three groups of the companies categorized by the exposure of their operations towards the regions of interest. Negative CARs are followed by a reversal effect on the first trading day following the event day. The CARs are the most negative for the companies having exposure to the WAC region (-0,0198 and t-value of -2,108), followed by the companies with the exposure to the U.S. only (-0,0140 and t-value of -6,114), and, followed by the companies with the exposure of their operations to Europe (-0,0101 with t-value of -6,887).

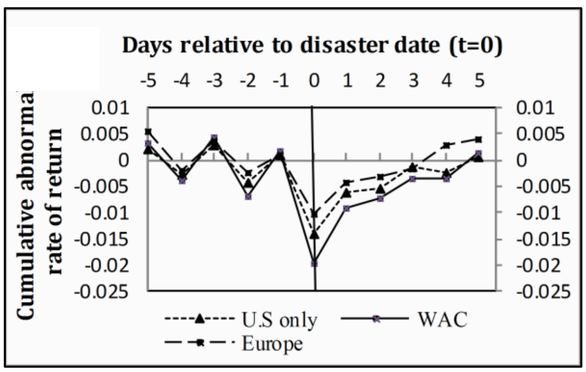
I use the two-factor model to match each company's CARs to the corresponding industry of operation and analyze whether the CARs are driven by the noise in the market (French and Roll, 1986). Similarly to the single factor model, the CARs for the companies with exposure of their operations to the U.S. only and to the WAC region are negative (-0,0145 with t-value of -6,163 for the U.S. and -0,0192 with t-value of -2,162 for the WAC region) and larger compared to the CARs for the companies with exposure of their operations to Europe (-0,0135 with t-value of -6,825). More evidence on these effects can be found in Table A.5.

In Figure 1.2b and 1.2c together with Panel 2 and Panel 3 of Table A.9.1, the portfolios of stocks are categorized by size and stock return volatility. Decile 10 (smallest firms) and decile 1 (highest volatility) show stronger negative CARs compared to the large and least volatile stocks (see also Tables A.6 and A.7). Furthermore, I find that aviation companies are the most negatively affected by the Ebola outbreak events whereas the companies producing healthcare equipment are on the other extreme and benefited the most (see Figure 1.2d, Table A.8 and Panel 4 of Table A.9.1 for more details). Lastly, the companies under the intense media coverage exhibit stronger negative and statistically significant CARs compared to the companies that are not exposed to the intense media coverage (see, Figure 1.2e). Under the intense media coverage, the trading volume, price range, and bid-ask spreads of the companies significantly increase around the event day (see Figure 1.2f, Table A.9 and Panel 6 of Table A.9.1).

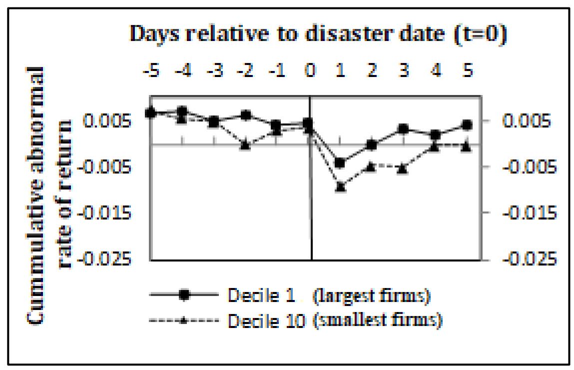
Overall, the event study analysis points to a negative impact of the Ebola outbreak events towards the U.S. companies' stock returns. I stress that the event study results are weaker than the regression results reported in the next section due to the fact that only 40 out of 103 events were employed in the CAR analysis—as a result of the event non-overlapping selection criteria.

Figure 1.2 Cumulative Abnormal Returns

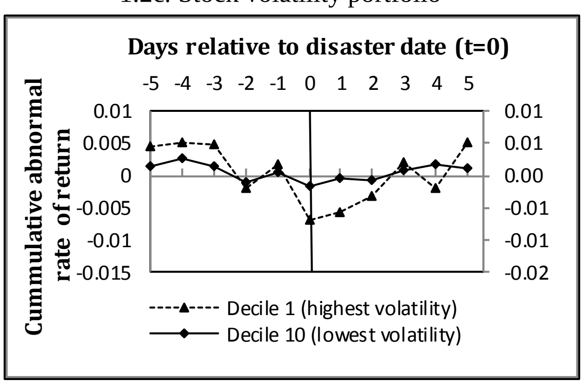
1.2a. Exposure towards geographic region portfolio



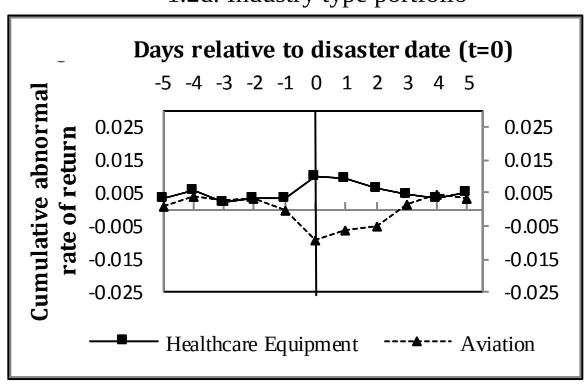
1.2b. Company size portfolio



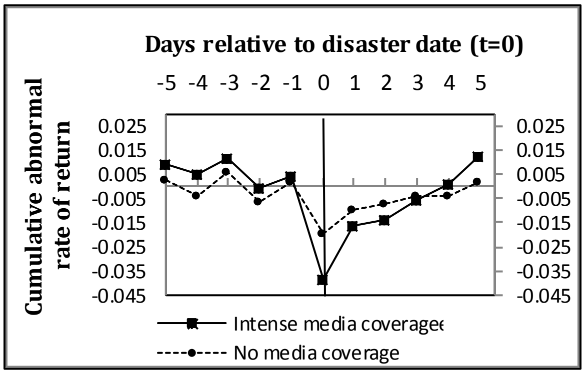
1.2c. Stock volatility portfolio



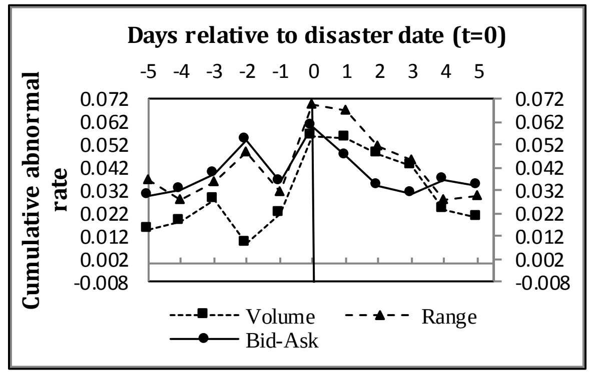
1.2d. Industry type portfolio



1.2e. High intensity of media coverage



1.2f. Volume, Price Range, Bid-Ask spread portfolios



Notes. Fig 1.2a – Fig 1.2e CARs around the event day ($\boldsymbol{t}$=0) for portfolios of companies categorized by exposure towards different geographic locations, by size, level of stock's volatility, industry of operation, and intensity of events' media coverage. Fig 1.2f depicts companies trading volume, price range, and bid-ask spreads under high intensity of media coverage. The abnormal return on day $\boldsymbol{t}$ is calculated as the difference between the observed rate of return and the ex-post expected rate of return on day $\boldsymbol{t}$. The one-factor market model $\boldsymbol{r_{it} = \alpha_0 + \beta_1 r_{m,t} + \varepsilon_t}$, where $\boldsymbol{r_{it}}$ is the return on stock $\boldsymbol{i}$ in period $\boldsymbol{t}$ and $\boldsymbol{r_{m,t}}$ is the S&P 500 return, is estimated using a 100-day estimation window. The event selection procedure follows the *last/first* occurrence criteria which yields to a total number of 40 event days with non-overlapping event windows during the 2014–2016 Ebola outbreak period

1.6.2 Geographic Proximity of Information and Financial Markets

Panel A of Table 1.1 summarizes the results of the regression analysis in (3). Panel B of Table 1.1 presents the results of the regression without control variables. Panel A of Table 1.1 reveals that daily-rate-of-return coefficients of the companies with exposure of their operations to all regions are negative and significant to all event locations at the day of the event (i.e., to the events located in the U.S., the WAC, and Europe). As expected, the regression coefficient is the largest and statistically significant at 5% level for the companies with exposure of their operations to the WAC region and for the events located in the WAC region and in the U.S. (-0.0261 and -0.0257 for the WAC and the U.S. based events, respectively). Interestingly, the companies with exposure of their operations to the U.S. only region strongly react to the events located on the U.S. soil but less strongly to the other event locations. The regression coefficients for the companies with the exposure of their operations to Europe and event location in Europe are negative and significant, but of smaller magnitude.

The results regarding the control variables serial correlation ($\sum_{j=1}^{5} r_{i,t-j}$), "Monday effects" ($\sum_{k=1}^{4} WD_{k,t}$), and "turn-of-the-year effect" (Tax_t) are similar to previous studies. The coefficients from lag 1 to lag 5, attributed to infrequent trading, happen to be both positive and negative and smaller compared to the coefficient on the event day. Similarly, the Monday coefficient is negative and the "turn-of-the-year effect" coefficient is positive and significant at least at 10% level. Coefficients for the other days of the week are mostly negative but insignificant (see Kaplanski and Levi, 2010b; Schwert, 1990a, 1990b for similar results).

Lastly, to control for possible reversal effects I run the regression analysis in (4) for the securities with exposure to different regions of interest but for all event locations at ones. From Panel A of Table A.10 I can observe that the rate of returns from the first three days following the main event day are still negative, weaker, and significant (with significance varying from 10% level to 1% level) indicating a reversal behavior (see, Panel A of Table A.10, coefficients of $E_{t,1}$, $E_{t,2}$, and $E_{t,3}$ for all regions of exposure). I record no statistically significant coefficients on the fourth and fifth day following the main event day. The results do not rule out the existence of an effect for the fourth and fifth day after the main event day but rather suggest that I could not observe it. This may be due to a small-time elapse between the events, greater variation in the period, and proliferation within the media.

To sum up, Table 1.1 accompanied by Table A.10 in the appendix A reveals that the event effect is present in all regions of interest and event locations. The stocks of the companies with exposure of their operations to the U.S. only and the WAC region exhibit a pronounced negative behavior, potentially as a result of the geographic proximity of the information to the financial markets. Furthermore, the tables show a reversal effect on the first day after the event day, persistent for three days and accompanied by negative/positive and statistically significant "Monday effects," "turn-of-the-year effect," and two-day significant serial correlation.

This provides support for my first hypothesis that the geographic proximity matters for the companies that are geographically closer to both the birthplace of the disease as well as to the financial market. There are two potential reasons for this. First, the investors feel that the U.S. only and the WAC region related companies are closer to the birthplace of the Ebola outbreak events, and thus, assume more relevance for (not) investing in them. Second, the media coverage affects investor sentiment especially for the companies with exposure of their operations to the U.S. and the WAC region than for the companies with exposure of their operations to Europe.

Table 1.1 Geographic proximity effect on financial markets
The table reports the results of the following regression:

$$r_{i,t} = \gamma_0 + \sum_{j=1}^{5} \gamma_{1,j} r_{i,t-j} + \sum_{k=1}^{4} \gamma_{2,k} WD_{k,t} + \gamma_3 Tax_t + \sum_{l=1}^{3} \gamma_{4,l} EL_{l,t} + \epsilon_t,$$

where $r_{i,t}$ is the rate of return of stock i on day t with exposure of its operations towards the U.S., the WAC region, Europe, or All regions, γ_0 is the regression intercept, $r_{i,t-j}$ is the lagged dependent variable—the jth previous day rate of return, $WD_{k,t}$ with $k = 1, \ldots, 4$ are dummy variables for the day of the week (Monday, Tuesday, Wednesday, and Thursday), Tax_t is a dummy variable for the first five days of the taxation year, and $EL_{l,t}$ with $l = 1, 2,$ and 3, are dummy variables that denote the location where the event happened and equal 1 on the event day if the event happened in a specific region (either in the U.S., the WAC region, and Europe), and zero otherwise. The events occurred during the 2014–2016 Ebola outbreak period (3-year period) and include a total number of 103 event days of the disease outbreak. From the total number of events, 52 took place in the WAC region, 31 in the U.S., and 20 in Europe. Panel A depicts the regression results including the control variables whereas Panel B depicts the regression results without the control variables. The first line reports the regression coefficients, while the second line reports the corresponding t-values (in brackets). One, two, and three asterisks indicate a significance level of 10%, 5%, and 1%, respectively.

PANEL A: Regression results including the control variables

Exposure of the company to	γ_0	R_{t-5}	R_{t-4}	R_{t-3}	R_{t-2}	R_{t-1}	**Mon.**	**Tue.**	**Wed.**	**Thu.**	**Tax**	**U.S.**	**WAC**	**Europe**	R^2
U.S. only	-0,0143 (-3,002***)	0,0129 (1,611)	-0,0132 (-0,923)	0,0283 (1,386)	-0,0111 (-1,783*)	0,0103 (3,448***)	-0,0231 (-1,976**)	-0,0133 (-1,252)	-0,0160 (-0,019)	-0,0211 (-1,213)	0,0285 (1,989**)	-0,0259 (-2,126**)	-0,0163 (-1,645*)	-0,0155 (-1,591)	0,4253
WAC region	-0,0522 (-2,752***)	0,0134 (1,604)	-0,0148 (-1,110)	0,0264 (1,113)	-0,0127 (-1,887*)	0,0118 (3,293***)	-0,0382 (-1,691*)	-0,0223 (-0,767)	-0,0122 (-0,238)	-0,0103 (-1,327)	0,0226 (1,663*)	-0,0257 (-2,108**)	-0,0261 (-1,970**)	-0,0204 (-1,690*)	0,5811
Europe	-0,0251 (-1,969**)	0,0153 (0,441)	-0,0128 (-1,019)	0,0245 (1,250)	-0,0102 (-1,665*)	0,0101 (1,959**)	-0,0201 (-1,675*)	-0,0115 (-1,116)	0,0150 (0,988)	-0,0118 (-1,235)	0,0150 (1,717*)	-0,0183 (-1,987**)	-0,0121 (-1,687*)	-0,0188 (-1,966**)	0,3736
All	-0,0308 (-1,977**)	0,0172 (0,071)	-0,0138 (-0,420)	0,0251 (0,532)	-0,0114 (-1,816*)	0.0099 (3,688***)	-0,0212 (-2,001**)	-0,0254 (-1,221)	0,0154 (0,350)	-0,0170 (-1,166)	0,0288 (1,842*)	-0,0232 (-2,020**)	-0,0229 (-1,965**)	-0,0157 (-1,780*)	0,2332

PANEL B: Regression results without the control variables

Exposure of the company to	γ_0	R_{t-5}	R_{t-4}	R_{t-3}	R_{t-2}	R_{t-1}	**Mon.**	**Tue.**	**Wed.**	**Thu.**	**Tax**	**U.S.**	**WAC**	**Europe**	R^2
U.S. only	-0,0125 (-3,339***)											-0,0255 (-3,317***)	-0,0151 (-1,662*)	-0,0148 (-1,550)	0,4436
WAC region	-0,0413 (-2,321**)											-0,0245 (-2,121**)	-0,0248 (-1,982**)	-0,0192 (-1,689*)	0,5921
Europe	-0,0210 (-1,995**)											-0,0161 (-1,992**)	-0,0119 (-1,682*)	-0,0176 (-1,964**)	0,3524
All	-0,0289 (-1,982**)											-0,0229 (-2,103**)	-0,0224 (-1,970**)	-0,0153 (-1,772*)	0,2531

1.6.3 Event Effect and Firm Size

Following Brown and Cliff (2005) and Edmans et al. (2007), I test whether the event effect is stronger for the stocks of small companies relative to the stocks of large companies. Table 1.2 reveals the regression results, where each dependent variable is the daily rate of return on a portfolio comprised of stocks belonging to a firm-size decile. Deciles rank from 1 to 10, where decile 1 is composed of the largest firms by size and decile 10 is composed of the smallest firms by size. Similar to previous studies (e.g., Schwert, 1990b), on the day of the event, the event effect coefficients (corresponding to event locations: the U.S., the WAC, and Europe) tend to increase as size decreases. The regression coefficients for firms in decile 1 are -0.0146, -0.0142, and -0.0132 for the events taking place in the U.S., the WAC, and Europe, respectively. The regression coefficients for firms in decile 10 are -0.0519, -0.0482, and -0.0328 for the events taking place in the U.S., the WAC, and Europe, respectively.

Regarding the control variables, the serial correlation coefficients for 1 and 2 lags corresponding to the largest stocks are positive and significant. These results correspond to those of Schwert (1990b), who finds significant serial correlations for these variables when analyzing the S&P's Composite Index. Furthermore, large (in absolute terms) and significant "Monday effect" as well as "turn-of-the-year effect" are recorded throughout all size deciles.
Lastly, to control for possible reversal effects I return to the regression analysis in (4). On the day following the event day, the gap between the most extreme portfolios widens even more, potentially as a result of an investor reaction to the previous day event (from -0.0140 for decile 1 to -0.0524 for decile 10). I observe statistically significant reversal effects up to the third trading day after the event day (see Table A.11 in the appendix A).

To sum up, Table 1.2 and Table A.11 in the appendix A report that the event effect is more pronounced for small stocks rather than for large stocks from the event day to three days later. A potential explanation could posit that the information dissemination of small stocks is poorer than the information dissemination of large stocks. Due to the disparity between the small and large stocks, media can especially influence small stocks, for which the information dissemination is limited. For large stocks, information dissemination channels are already well-established, and the role of media is more restrained (Fang and Peress, 2009).

Table 1.2 Stocks classified by size

The table reports the results of the following regression:

$$r_{i,t} = \gamma_0 + \sum_{j=1}^{5} \gamma_{1,j} r_{i,t-j} + \sum_{k=1}^{4} \gamma_{2,k} WD_{k,t} + \gamma_3 Tax_t + \sum_{l=1}^{3} \gamma_{4,l} EL_{l,t} + \epsilon_t,$$

where $r_{i,t}$ is the rate of return of stock i on day t classified by size, γ_0 is the regression intercept, $r_{i,t-j}$ is the lagged dependent variable—the jth previous day rate of return, $WD_{k,t}$ with $k = 1, \dots, 4$ are dummy variables for the day of the week (Monday, Tuesday, Wednesday, and Thursday), Tax_t is a dummy variable for the first five days of the taxation year, and $EL_{l,t}$ with $l = 1, 2,$ and 3, are dummy variables that denote the location where the event happened and equal 1 on the event day if the event happened in a specific region (either in the U.S., the WAC region, and Europe), and zero otherwise. The events occurred during the 2014–2016 Ebola outbreak period (3-year period) and include a total number of 103 event days of the disease outbreak. From the total number of events, 52 took place in the WAC region, 31 in the U.S., and 20 in Europe. The first line reports the regression coefficients, while the second line reports the corresponding t-values (in brackets). One, two, and three asterisks indicate a significance level of 10%, 5%, and 1%, respectively.

Size Decile	γ_0	R_{t-5}	R_{t-4}	R_{t-3}	R_{t-2}	R_{t-1}	Mon.	Tue.	Wed.	Thu.	Tax	U.S.	WAC	Europe	R^2
Decile 1 (largest firms)	-0,0233 (-1,672*)	0,0651 (0,824)	0,0731 (0,243)	0,0541 (1,456)	0,0639 (1,667*)	0,0133 (1,644*)	-0,0167 (-1,962**)	0,0052 (1,012)	-0,0033 (-1,246)	-0,0032 (-0,502)	0,0234 (1,998**)	-0,0146 (-2,264**)	-0,0142 (-2,223**)	-0,0132 (-1,210)	0,2769
Decile 2	-0,0432 (-1,831*)	0,0932 (0,467)	-0,0083 (-1,448)	0,0073 (1,484)	-0,0137 (-1,103)	0,0148 (1,044)	-0,0235 (-2,651***)	0,0101 (1,314)	-0,0023 (-1,223)	-0,0081 (-0,107)	0,0563 (1,657*)	-0,0255 (-3,030***)	-0,0245 (-2,191**)	-0,0182 (-1,932*)	0,4053
Decile 3	-0,0631 (-1,615)	0,0464 (0,902)	-0,0045 (-1,522)	0,0562 (1,100)	-0,0015 (-1,895*)	0,0342 (1,683*)	-0,0257 (-2,138**)	0,0749 (0,033)	0,0145 (0,214)	-0,0091 (-1,134)	0,0203 (1,774*)	-0,0243 (-2,247**)	-0,0235 (-1,645*)	-0,0141 (-1,767*)	0,3143
Decile 4	-0,0320 (-1,854*)	0,0235 (0,440)	0,0142 (1,639)	-0,0235 (-1,566)	-0,0266 (-1,535)	0,0255 (1,214)	-0,0160 (-1,767*)	0,0219 (0,036)	0,0056 (1,261)	-0,0057 (-0,145)	0,0256 (1,872*)	-0,0209 (-1,975**)	-0,0113 (-2,321**)	-0,0092 (-1,651*)	0,2869
Decile 5	-0,0241 (-2,146**)	0,0334 (1,462)	0,0407 (0,375)	0,0448 (1,244)	-0,0197 (-1,683*)	0,0134 (2,213**)	0,0282 (-1,755*)	0,0535 (0,122)	0,0035 (1,425)	-0,0065 (-1,534)	0,0251 (1,893*)	-0,0284 (-2,128**)	-0,0274 (-1,696*)	-0,0155 (-1,207)	0,1398
Decile 6	-0,0657 (-1,953*)	0,0376 (1,574)	0,0775 (1,342)	0,0185 (1,183)	0,0494 (1,356)	0,0135 (2,532**)	-0,0321 (-1,655*)	-0,0425 (-0,134)	0,0045 (1,124)	-0,0126 (-0,153)	0,0221 (1,854*)	-0,0333 (-2,351**)	-0,0312 (-2,253**)	-0,0161 (-1,659*)	0,4624
Decile 7	-0,0442 (-1,880*)	0,0445 (0,102)	0,0182 (0,944)	0,0164 (1,171)	-0,0243 (-1,567)	0,0113 (1,979**)	-0,0344 (-2,201**)	0,0545 (0,423)	0,0147 (0,050)	-0,0013 (-0,352)	0,0159 (1,968**)	-0,0353 (-2,121**)	-0,0313 (-1,961*)	-0,0113 (-1,221)	0,4840
Decile 8	-0,0366 (-1,975**)	0,0514 (0,037)	-0,0463 (-1,284)	0,0132 (0,219)	-0,0268 (-1,872*)	0,0126 (1,867*)	-0,0332 (-1,742*)	-0,0236 (-0,371)	-0,0061 (-0,236)	-0,0062 (-0,454)	0,0174 (1,662*)	-0,0384 (-4,124***)	-0,0337 (-1,876*)	-0,0312 (-1,910*)	0,3343
Decile 9	-0,0312 (1,673*)	0,0258 (1,123)	-0,0233 (-1,361)	-0,0287 (-1,340)	0,0139 (1,681*)	0,0246 (1,976**)	-0,0412 (-1,659*)	-0,0121 (-0,130)	-0,0081 (-0,107)	-0,0044 (-1,571)	0,0123 (1,871*)	-0,0459 (-4,053***)	-0,0410 (-2,519**)	-0,0324 (-1,695*)	0,1214
Decile 10 (smallest firms)	-0,0421 (-1,741*)	0,0271 (0,490)	0,0558 (0,467)	0,0284 (1,026)	-0,0239 (-1,852*)	0,0323 (2,421**)	-0,0487 (-2,252**)	-0,0462 (-1,428)	-0,0091 (-1,134)	-0,0035 (-0,038)	0,0132 (1,851*)	-0,0519 (-2,916***)	-0,0482 (-2,238**)	-0,0328 (-1,966**)	0,2502

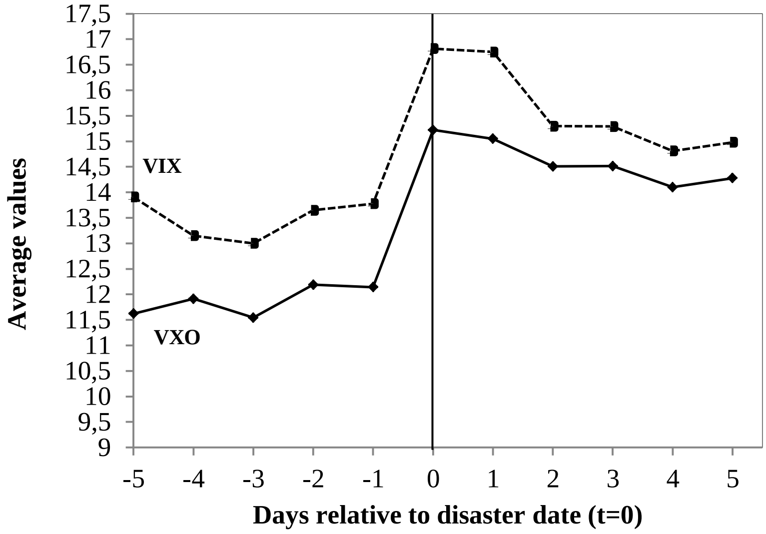
1.6.4 Event Effect on Implied Volatility (VIX and VXO)

Following Baker and Wurgler (2007) who use implied volatility as a proxy for investor sentiment, I next test whether Ebola outbreak events affect the implied volatility. I employ two measures of the fear index,[13] the VIX and VXO (see Whaley, 2000).

Figure 1.3 shows the aggregated volatility pattern around the event days. It reveals a strong effect on the day of the event (at t=0) and a mild persistence of the effect on the first day following the event day. In addition, I do not observe a return to the prevailing average value before the event. This result complies with previous findings showing that the market volatility is persistent (e.g., Baker and Wurgler, 2007). To test the significance of the volatility represented by VIX and VXO, I employ a matched-pair t-test. I observe statistically significant increase in volatility on the event day with t-values of $t=4.579$ ($P<0.001$) and $t=4.013$ ($P<0.028$) for VIX and VXO respectively.

My results might indicate that the rapid increase in the implied volatility on the event day is due to a mood effect induced by the Ebola outbreak events. However, the increase in the volatility may also be due to an increase in the actual market volatility, which may coincidentally occur at the same time as the Ebola outbreak. For example, Schwert (2003) analyzes a long-time period of market volatility and finds that the monthly stock volatility was higher during banking crises and economic recessions. In my case, there may be other reasons for increased market volatility around the event day if an Ebola outbreak effect is related to some confounding variables (e.g., stock market crashes or economic crises).

Figure 1.3. Fear Index Around the Event Days



Notes. The figure depicts the average value of VIX and VXO indices around the event day (t=0). The 2014–2016 Ebola outbreak period is covered. It includes 40 non-overlapping events of the total 103 events.

[13] Fear Index was launched by the Chicago Board of Options Exchange (CBOE) in 1993. VIX depends on the average price of the options written on the broader S&P500 Index whereas VXO depends on the average implied volatility of the options on the S&P100 Index as measured by the Black-Scholes (1973) model.

1.6.5 Event Effect and Company Risk

Baker and Wurgler (2007) study the impact of investor sentiment on a cross-section of stock returns. They find that investor sentiment has a stronger effect upon the securities with valuations that are difficult to arbitrage and subjective to evaluate. Inspired by their study, I examine the Ebola outbreak event effect on various groups of stocks (volatile vs. non-volatile). Table 1.3 reports the results, where each dependent variable is the daily rate of return on a portfolio composed of stocks that are divided into 10 deciles with respect to stock volatility. Decile 1 includes the most volatile and decile 10 includes the least volatile stocks.

The results show that the event effect is intact for all deciles, except for decile 7. The regression coefficient on the day of the event is larger, negative, and highly significant for the most volatile stocks compared to the regression coefficient for the less volatile stocks, which is consistent with my third hypothesis in Section 1.5.

Regarding the control variables, "Monday effect" as well as "turn-of-the-year effect" variables show negative and statistically significant presence in stocks' volatility for each portfolio employed.

The results of the regression in (4) are presented in Table A.12 in the appendix A. The coefficients for the days following the event day follow similar pattern. That is, the event effect magnitude is larger, negative, and significant for the stocks belonging to the highest volatility decile than for the stocks belonging to the least volatile decile.

1.6.6 Event Effect on the U.S. Industries

Table 1.4 reveals the regression results where stocks are classified by different industries. On the day of the event (for the events taking place in the U.S., the WAC, and Europe), all coefficients are large, negative, and significant, except for Healthcare equipment, Pharmaceutical, Biotechnology, and Food & Beverage industry. The stock returns of these four industries are positively affected by the Ebola outbreak. The results from Table 1.4 confirm my expectations, revealing evidence for the industry effect.

A potential explanation is that investors anticipate an increase in cash flows for the industries due to, for example, investing in R&D or selling new medicines aimed at fighting the new pandemic disease. The results are related to Hirshleifer et al. (2013) who find that innovative efficiency and citations scaled by R&D expenditures positively determine future stock returns. A conclusion would be that the investor sentiment about the performance of certain industries may be an important element that drives investment decisions.

Table 1.3 Stocks classified by volatility

The table reports the results of the following regression:

$r_{i,t} = \gamma_0 + \sum_{j=1}^{5}\gamma_{1,j}r_{i,t-j} + \sum_{k=1}^{4}\gamma_{2,k}WD_{k,t} + \gamma_3 Tax_t + \sum_{l=1}^{3}\gamma_{4,l}EL_{l,t} + \epsilon_t,$

where $r_{i,t}$ is the rate of return of stock i on day t classified by volatility, γ_0 is the regression intercept, $r_{i,t-j}$ is the lagged dependent variable—the jth previous day rate of return, $WD_{k,t}$ with $k = 1, \dots, 4$ are dummy variables for the day of the week (Monday, Tuesday, Wednesday, and Thursday), Tax_t is a dummy variable for the first five days of the taxation year, and $EL_{l,t}$ with $l = 1, 2,$ and 3, are dummy variables that denote the location where the event happened and equal 1 on the event day if the event happened in a specific region (either in the U.S., the WAC region, and Europe), and zero otherwise. The events occurred during the 2014–2016 Ebola outbreak period (3-year period) and include a total number of 103 event days of the disease outbreak. From the total number of events, 52 took place in the WAC region, 31 in the U.S., and 20 in Europe. The first line reports the regression coefficients whereas the second line reports the corresponding t-values (in brackets). One, two, and three asterisks indicate a significance level of 10%, 5%, and 1%, respectively.

Volatility Decile	γ_0	R_{t-5}	R_{t-4}	R_{t-3}	R_{t-2}	R_{t-1}	Mon.	Tue.	Wed.	Thu.	Tax	U.S.	WAC	Europe	R^2
Decile 1 (highest volatility)	-0,0831 (-2,212**)	0,0240 (1,647*)	0,0232 (1,532)	0,0136 (1,653*)	-0,0131 (-2,321**)	0,0018 (1,962**)	-0,0133 (-1,652*)	-0,0132 (-1,732*)	-0,0124 (-0,501)	-0,0131 (-1,231)	0,0136 (1,972**)	-0,0492 (-2,135**)	-0,0463 (-2,341**)	-0,0401 (-1,742*)	0,3232
Decile 2	-0,0821 (-2,335**)	0,0147 (1,998**)	0,0244 (1,064)	0,0124 (1,647*)	-0,0126 (-2,025**)	0,0013 (1,714*)	-0,0128 (-2,230**)	-0,0127 (-1,754*)	-0,0122 (-0,627)	-0,0119 (-1,024)	0,0135 (1,863*)	-0,0483 (-1,971**)	-0,0415 (-1,652*)	-0,0385 (-2,074**)	0,5124
Decile 3	-0,0366 (-1,975**)	0,0213 (0,049)	-0,0463 (-1,284)	0,0139 (1,229)	-0,0268 (-1,872*)	0,0116 (1,864*)	-0,0132 (-1,642*)	-0,0236 (-0,371)	-0,0061 (-0,236)	-0,0062 (-0,454)	0,0183 (1,645*)	-0,0462 (-2,123**)	-0,0367 (-1,865*)	-0,0217 (-1,934*)	0,3021
Decile 4	-0,0442 (-1,880*)	0,0445 (1,235)	0,0482 (0,944)	0,0123 (1,142)	-0,0243 (-1,567)	0,0125 (1,968**)	-0,0130 (-2,109**)	0,0545 (0,423)	0,0147 (0,050)	-0,0013 (-0,352)	0,0161 (1,974**)	-0,0414 (-2,092**)	-0,0333 (-1,960*)	-0,0223 (-0,323)	0,4840
Decile 5	-0,0342 (-2,351**)	0,0135 (1,646*)	0,0239 (1,437)	0,0122 (0,365)	-0,0112 (-1,932*)	0,0022 (1,520)	-0,0116 (-1,851*)	-0,0111 (-1,238)	-0,0115 (-0,231)	-0,0065 (-1,534)	0,0124 (1,725*)	-0,0369 (-2,303**)	-0,0292 (-3,352***)	-0,0266 (-1,651*)	0,4157
Decile 6	-0,0133 (-1,966**)	0,0144 (1,667*)	0,0231 (0,234)	0,0127 (0,325)	-0,0114 (-2,643**)	0,0023 (0,127)	-0,0108 (-1,644*)	-0,0107 (-0,025)	-0,0110 (-0,019)	-0,0126 (-0,153)	0,0122 (1,643*)	-0,0271 (-2,152**)	-0,0235 (-4,230***)	-0,0261 (-1,845*)	0,1208
Decile 7	0,0128 (1,646*)	0,0132 (1,714*)	0,0117 (1,872*)	0,0110 (1,262)	-0,0113 (-4,119***)	0,0009 (1,649*)	-0,0113 (-1,742*)	-0,0105 (-1,051)	-0,0108 (-0,864)	-0,0013 (-0,352)	0,0103 (1,965**)	-0,0247 (-1,563)	-0,0219 (-1,421)	0,0249 (1,138)	0,6121
Decile 8	0,0131 (2,524**)	0,0123 (1,842*)	0,0106 (1,971**)	0,0104 (0,103)	-0,0111 (-1,742*)	0,0012 (1,861*)	-0,0121 (-1,821*)	-0,0105 (-1,203)	-0,0103 (-1,243)	-0,0105 (-0,028)	0,0095 (1,742*)	-0,0236 (-1,976**)	-0,0216 (-3,915***)	-0,0227 (-1,163*)	0,3343
Decile 9	0,0125 (3,348***)	0,0103 (1,994**)	0,0112 (2,643***)	0,0119 (1,977**)	-0,0114 (-1,205)	0,0014 (1,763*)	-0,0110 (-1,974**)	-0,0104 (-1,735*)	-0,0107 (-1,023)	-0,0085 (-1,162)	0,0089 (1,667*)	-0,0177 (-1,983**)	-0,0108 (-2,202**)	-0,018 (-1,677*)	0,2915
Decile 10 (lowest volatility)	0,0123 (3,224***)	0,0132 (1,653*)	0,0110 (2,284**)	0,0112 (3,095***)	-0,0110 (-2,128**)	0,0016 (1,981**)	-0,0102 (-1,750*)	-0,0105 (-1,767*)	-0,0106 (-1,362)	-0,0100 (-1,046)	0,0033 (1,560)	-0,0149 (-2,214**)	-0,0109 (-1,750*)	-0,0103 (-1,652*)	0,4512

Table 1.4 Event effect on U.S. Industries

The table reports the results of the following regression:

$$r_{i,t} = \gamma_0 + \sum_{j=1}^{5} \gamma_{1,j} r_{i,t-j} + \sum_{k=1}^{4} \gamma_{2,k} WD_{k,t} + \gamma_3 Tax_t + \sum_{l=1}^{3} \gamma_{4,l} EL_{l,t} + \epsilon_t,$$

where $r_{i,t}$ is the rate of return of stock *i* on day *t* classified by industry of operation, γ_0 is the regression intercept, $r_{i,t-j}$ is the lagged dependent variable—the *j*th previous day rate of return, $WD_{k,t}$ with $k = 1, \dots, 4$ are dummy variables for the day of the week (Monday, Tuesday, Wednesday, and Thursday), Tax_t is a dummy variable for the first five days of the taxation year, and $EL_{l,t}$ with $l = 1, 2,$ and 3, are dummy variables that denote the location where the event happened and equal 1 on the event day if the event happened in a specific region (either in the U.S., the WAC region, and Europe), and zero otherwise. The events occurred during the 2014–2016 Ebola outbreak period (3-year period) and include a total number of 103 event days of the disease outbreak. From the total number of events, 52 took place in the WAC region, 31 in the U.S., and 20 in Europe. The first line reports the regression coefficients, while the second line reports the corresponding t-values (in brackets). One, two, and three asterisks indicate a significance level of 10%, 5%, and 1%, respectively. The industries have been selected by their contribution to the U.S. GDP. Below presented, are the 12 largest by contribution industries according to S&P Dow Jones Industry Indexes.

Industry name	γ_0	R_{t-5}	R_{t-4}	R_{t-3}	R_{t-2}	R_{t-1}	Mon.	Tue.	Wed.	Thu.	Tax	U.S.	WAC	Europe	R^2
Capital Markets	-0,0321 (-2,225**)	0,0136 (0,221)	0,0126 (1,076)	0,0153 (0,442)	0,0145 (1,044)	0,0124 (2,132**)	-0,0153 (-1,752*)	-0,0113 (-1,322)	-0,0134 (-1,231)	-0,0163 (-1,467)	0,0135 (1,243)	-0,0121 (-2,143**)	-0,0131 (-1,662*)	-0,0122 (-1,915*)	0,3509
Healthcare Equipment	0,0448 (1,854*)	0,0163 (1,647*)	0,0165 (1,057)	0,0164 (1,657*)	0,0127 (1,794*)	0,0145 (2,116**)	0,0123 (1,982**)	0,0142 (1,544)	0,0216 (0,224)	-0,0134 (-0,304)	0,0131 (1,310)	0,0249 (1,971**)	0,0251 (2,320**)	0,0224 (1,757*)	0,4291
Crude Oil	-0,0563 (-1,542)	-0,0147 (-2,202**)	-0,0167 (-2,356**)	-0,0145 (-1,845*)	-0,0134 (-1,656*)	0,0019 (1,673*)	-0,0126 (-1,929*)	-0,0156 (-1,230)	-0,0145 (-1,021)	0,0147 (1,367)	0,0038 (1,674*)	-0,0125 (-1,962**)	-0,0164 (-1,646*)	-0,0112 (-1,722*)	0,2376
Industrials	-0,0474 (-2,639**)	-0,0192 (-1,687*)	-0,0154 (-0,341)	-0,0173 (-1,532)	-0,0143 (-0,013)	0,0121 (1,676*)	-0,0138 (-1,785*)	-0,0134 (-0,174)	-0,0132 (-1,447)	0,0264 (1,456)	0,0236 (0,085)	-0,0159 (-1,983**)	-0,0163 (-1,965**)	-0,0134 (-1,826*)	0,2049
Materials	-0,0121 (-1,843*)	-0,0125 (-1,941*)	-0,0147 (-1,667*)	-0,0162 (-2,162**)	-0,0145 (-1,992**)	-0,0119 (-2,223**)	-0,0108 (-1,662*)	-0,0113 (-1,025)	-0,0122 (-1,152)	0,0155 (1,357)	0,0134 (1,279)	-0,0147 (-1,960**)	-0,0151 (-1,742*)	-0,0128 (-1,646*)	0,3516
Information Technology	0,0437 (2,220**)	-0,0131 (-1,422)	0,0143 (1,342)	-0,0157 (-0,235)	-0,0122 (-1,962**)	-0,0115 (1,654*)	-0,0143 (-1,685*)	-0,0164 (-0,432)	-0,0126 (-1,227)	0,0143 (1,574)	0,0205 (1,621)	-0,0156 (-2,311**)	-0,0138 (-1,321)	-0,0122 (-1,752*)	0,2941
Utilities	-0,0215 (-1,556)	0,0119 (1,508)	0,0146 (1,842*)	-0,0177 (-1,662*)	-0,0175 (-1,114)	0,0114 (1,961**)	-0,0152 (-1,651*)	-0,0145 (-1,475)	-0,0132 (-1,121)	-0,0124 (-1,042)	-0,0192 (-1,325)	-0,0138 (-1,970**)	-0,0137 (-1,651*)	-0,0118 (-1,885*)	0,1308
Energy	-0,0594 (-1,967**)	-0,0124 (-1,654*)	-0,0138 (-1,412)	-0,0153 (-1,748*)	-0,0139 (-1,894*)	-0,0110 (-1,702*)	-0,0149 (-1,822*)	-0,0156 (-1,657)	-0,0132 (-1,421)	-0,0158 (-1,441)	-0,0102 (-1,474)	-0,0162 (-1,667*)	-0,0142 (1,644*)	-0,0127 (1,667*)	0,3257
Food & Beverage	0,0233 (2,274**)	-0,0112 (-1,338)	-0,0124 (-1,255)	-0,0242 (-0,497)	-0,0135 (-1,733*)	0,0124 (1,948*)	0,0132 (1,758*)	0,0142 (1,436)	0,0136 (1,705)	0,0114 (1,156)	0,0207 (1,648*)	0,0172 (1,972**)	0,0167 (1,981**)	0,0144 (1,740*)	0,4452
Aviation	-0,0652 (-1,995**)	-0,0123 (-1,445)	0,0130 (1,501)	0,0157 (1,358)	0,0134 (1,345)	0,0163 (1,927*)	-0,0121 (-1,672*)	-0,0129 (-1,525)	0,0157 (1,116)	0,0133 (0,248)	-0,0252 (-1,963**)	-0,0329 (-1,965**)	-0,0332 (-2,104**)	-0,0243 (-1,655*)	0,3640
Pharma.	0,0420 (1,861*)	0,0132 (1,734*)	0,0134 (1,656*)	0,0124 (1,666*)	0,0213 (1,232)	0,0150 (1,911*)	0,0155 (2,014**)	0,0126 (1,505)	0,0138 (1,543)	0,0148 (1,233)	0,0151 (1,712*)	0,0186 (1,841*)	0,0192 (2,664***)	0,0188 (2,229**)	0,3321
Biotech.	0,0461 (1,772*)	0,0133 (1,854*)	0,0244 (1,716*)	0,0144 (1,649*)	0,0216 (1,101)	0,0211 (2,218**)	0,0208 (1,954*)	0,0214 (1,056)	0,0072 (1,127)	0,0132 (1,521)	0,0188 (1,991**)	0,0147 (2,112**)	0,0149 (1,987**)	0,0136 (2,662***)	0,2825

1.6.7 Event Effect and Media Coverage

Following Kaplanski and Levy (2010b), I search the media for articles related to the Ebola outbreak disease to understand the scale and timing of the information salience and to evaluate the media coverage as a potential source of investor sentiment. Figure 1.4a and Figure 1.4b illustrate the number and frequency of media published articles about the Ebola outbreak.

The number of articles published by the three most circulated U.S. newspapers increases rapidly in the year of 2014 (see Figure 1.4a). In addition, the frequency of relevant news articles increases notably on the event day (see Figure 1.4b). The news coverage intensifies in the next three days, having its maximum on the first day after the event day. The purpose of this observation is twofold. First, it supports the events' intense media coverage presence. Second, it indicates the presence of sentiment effects.

I test whether the companies exposed to the intense media coverage are more affected by the Ebola outbreak events than the ones receiving less media exposure. The stock price reactions to the events are stronger for securities that are exposed to intense media coverage (see Panel A and Panel B of Table 1.5). In particular, the regression coefficients for the dummy variable $EL_{l,t}$ indicating the day of the event in different regions are higher for the securities exposed to the intense media coverage than for securities without the intense media coverage.

To check the persistency of the media effect, I employ the regression analysis in (4). The results are presented in Table A.14 in the appendix A. I find that the coefficients are higher for the events with the intense media coverage than for the events without intense media coverage, but the persistency of the effect is the same. These results support the role of the intense media coverage but also highlight possible sentiment effects.

On the one side, the Ebola outbreak events were publicly available on the day of the event and were absorbed in the market. On the other side, there is a persistence of the effect on the days following the event day. On these days, when the media is usually flooded with information on possibly disastrous causalities accompanied with live streaming and pictures, I detect a negative effect but of a smaller magnitude.

Table A.9 in the appendix A presents the results of the event study methodology that observe the impact of the intense media coverage on securities' performance around the event dates. Trading volume as a proxy for trading intensity shows an erratic behavior one day before the event day and up until three days after the event. Past research documents that unexpected and high-consequence events contribute to the trade turbulence in the markets increasing the volume of trades exponentially (Peress, 2014). The coefficients of the proxies for stock variability and liquidity—the price range and the bid-ask spread—increase only on the day of the event and they trend downward subsequently. This is consistent with my hypothesis that intense media coverage significantly affects stock returns, trading volume, stock liquidity, and stock variability and corroborates the results by Fang and Peress (2009).

To sum up, my results support the view that not only the event but also the intensity of the media coverage induces the effect in the stock market. The collective fear and shock of the disastrous event amplify the consequences of the event itself.

Figure 1.4 Articles Published

Number of Articles published on "Ebola outbreak"			
Year	**NYT**	**WSJ**	**WP**
2014	232	69	200
2015	93	8	47
2016	18	1	1

Fig. 1.4a

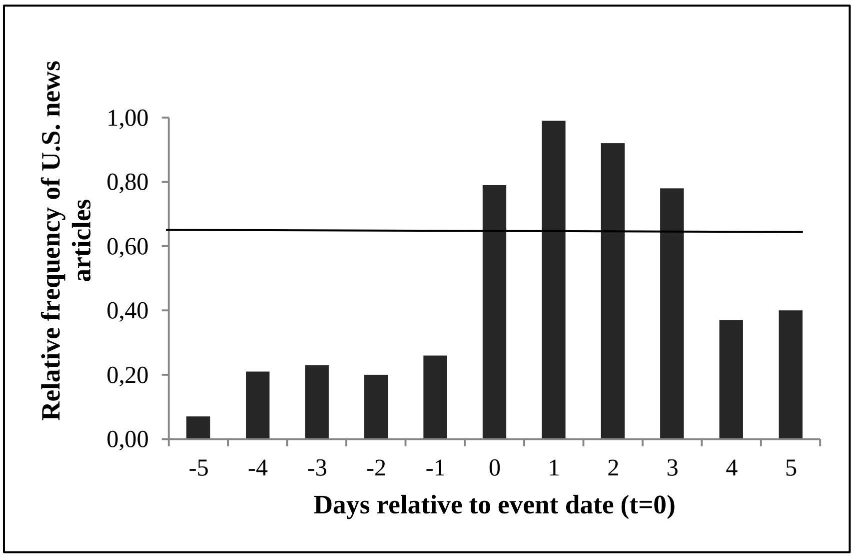


Fig. 1.4b

Notes. Fig 1.4a represents the number of articles published on the "Ebola outbreak" in the New York Times, Wall Street Journal, and Washington Post newspapers during the years 2014–2016. Fig 1.4b depicts the normalized number of distinct, Ebola outbreak related newspaper articles published in the above-mentioned newspapers. The event dates (denoted as t=0) are considered to be the official PHEIC statements. The number of articles is normalized relative to its peak value over the 11-day period. The black horizontal line represents the threshold level of 70% LexisNexis frequency of publishing score. Data is obtained using the LexisNexis database for global news and business information.

Table 1.5 Intense media coverage effects on company securities
The table reports the results of the following regression:

$r_{i,t} = \gamma_0 + \sum_{j=1}^{5}\gamma_{1,j}r_{i,t-j} + \sum_{k=1}^{4}\gamma_{2,k}WD_{k,t} + \gamma_3 Tax_t + \sum_{l=1}^{3}\gamma_{4,l}EL_{l,t} + \epsilon_t,$

where $r_{i,t}$ is the rate of return of stock i on day t with exposure of its operations towards the U.S., the WAC region, Europe, or All regions, γ_0 is the regression intercept, $r_{i,t-j}$ is the lagged dependent variable—the *j*th previous day rate of return, $WD_{k,t}$ with $k = 1, \dots, 4$ are dummy variables for the day of the week (Monday, Tuesday, Wednesday, and Thursday), Tax_t is a dummy variable for the first five days of the taxation year, and $EL_{l,t}$ with $l = 1, 2,$ and 3, are dummy variables that denote the location where the event happened and equal 1 on the event day if the event happened in a specific region (either in the U.S., the WAC region, and Europe), and zero otherwise. The events occurred during the 2014–2016 Ebola outbreak period (3-year period) and include a total number of 103 event days of the disease outbreak. From the total number of events, 52 took place in the WAC region, 31 in the U.S., and 20 in Europe. Panel A depicts the regression results from the events and stocks without the intense media coverage (as in Panel A of Table 1.1) whereas Panel B depicts the regression results of the stocks with intense media coverage. The first line reports the regression coefficients whereas the second line reports the corresponding t-values (in brackets). One, two, and three asterisks indicate a significance level of 10%, 5%, and 1%, respectively.

Exposure of the company to	γ_0	R_{t-5}	R_{t-4}	R_{t-3}	R_{t-2}	R_{t-1}	Mon.	Tue.	Wed.	Thu.	Tax	U.S.	WAC	Europe	R^2
PANEL A: Regression results from events without intense media coverage															
U.S. only	-0,0143	0,0129	-0,0132	0,0283	-0,0111	0,0103	-0,0231	-0,0133	-0,0160	-0,0211	0.0285	-0,0259	-0,0163	-0, 0155	0,4253
	(-3,002***)	(1,611)	(-0,923)	(1,386)	(-1,783*)	(3,448***)	(-1,976**)	(-1,252)	(-0,019)	(-1,213)	(1,989**)	(-3,126***)	(-1,645*)	(-1,591)	
WAC region	-0,0522	0,0134	-0,0148	0,0264	-0,0127	0,0118	-0,0382	-0,0223	-0,0122	-0,0103	0,0226	-0,0257	-0,0261	-0,0204	0,5811
	(-2,752***)	(1,604)	(-1,110)	(1,113)	(-1,887*)	(3,293***)	(-1,691*)	(-0,767)	(-0,238)	(-1,327)	(1,663*)	(-2,108**)	(-1,970**)	(-1,690*)	
Europe	-0,0251	0,0153	-0,0125	0,0245	-0,0102	0,0101	-0,0201	-0,0115	0,0150	-0,0118	0,0150	-0,0183	-0,0121	-0,0188	0,3736
	(-1,969**)	(0,441)	(-1,019)	(1,250)	(-1,665*)	(1,959**)	(-1,675*)	(-1,116)	(0,988)	(-1,235)	(1,717*)	(-1,987**)	(-1,687*)	(-1,966**)	
All	-0,0308	0,0172	-0,0136	0,0251	-0,0114	0.0099	-0.0212	-0.0254	0.0154	-0.0170	0.0288	-0.0232	-0,0229	-0,0157	0.2332
	(-1,977**)	(0,071)	(-0,420)	(0,532)	(-1,816*)	(3,688***)	(-2.001**)	(-1.221)	(0.350)	(-1.166)	(1.842*)	(-2,020**)	(-1,965**)	(-1,780*)	
PANEL B: Regression results from events with intense media coverage															
U.S. only	-0,0283	0,0236	-0,0217	0,0238	-0,0213	0,0210	-0,0263	-0,0126	-0,0282	-0,0341	0.0332	-0,0302	-0,0291	-0, 0258	0,4146
	(-3,132***)	(1,429)	(-0,910)	(1,268)	(-1,736*)	(3,136***)	(-1,988**)	(-1,200)	(-1,019)	(-1,234)	(1,974**)	(-3,122***)	(-1,992**)	(-1,647*)	
WAC region	-0,0538	0,0375	-0,0249	0,0346	-0,0319	0,0315	-0,0390	-0,0205	-0,0211	-0,0321	0,0271	-0,0349	-0,0352	-0,0216	0,3395
	(-2,334**)	(1,436)	(-1,519)	(1,131)	(-1,935*)	(1,958*)	(-1,661*)	(-1,272)	(-0,105)	(-1,207)	(1,675*)	(-3,011***)	(-1,971**)	(-1,652*)	
Europe	-0,0327	0,0254	-0,0221	0,0354	-0,0207	0,0202	-0,0227	-0,0121	0,0217	-0,0436	0,0235	-0,0215	-0,0223	-0,0239	0,3217
	(-1,962**)	(0,430)	(-0,013)	(1,223)	(-1,726*)	(1,923*)	(-1,773*)	(-1,156)	(1,018)	(-1,255)	(1,717*)	(-2,738***)	(-2,104**)	(-1,668*)	
All	-0,0320	0,0291	-0,0218	0,0315	-0,0245	0,0105	-0.0231	-0.0265	0.0252	-0.0431	0.0260	-0.0341	-0,0337	-0,0264	0.2931
	(-1,976**)	(1,301)	(-1,146)	(1,138)	(-3,128***)	(3,207***)	(-2.120**)	(-0.134)	(1.058)	(-1.186)	(1.826*)	(-1,962**)	(-1,985**)	(-1,802*)	

1.7 Concluding remarks

In this chapter, I find that the 2014–2016 Ebola outbreak events are followed by negative returns in the financial markets. Motivated by the studies showing that extreme events (e.g., aviation disasters, international sporting games, newspapers strikes; see Kaplanski and Levy, 2010a and 2010b; Edmans et al., 2007, and Peress, 2014) may impose a strong transitory decline in the financial markets which is very different from the direct economic loss, I look for an explanation in the realm of behavioral finance. Indeed, behavioral finance studies show that the media coverage of drastic events such as Ebola outbreak events can enhance anxiety, bad mood, and fear which may induce risk aversion and pessimism among the investors.

I confirm that the geographic proximity of the information to the financial markets increases the importance of the event (related to the 2014–2016 Ebola outbreak) and its impact on companies' stock returns. I find that the event effect is present in all regions of interest. It is larger and statistically significant for the companies with exposure of their operations to the U.S. only and the WAC region as well as for the events located in these two regions, than for the events located in Europe and for the companies with exposure of their operations to Europe. Additional tests on the event effects reveal that the market sentiment has a larger effect on more volatile stocks, stocks with highly subjective valuations, stocks of small firms, and stocks of firms belonging to specific industries.

It is possible that the bad mood and anxiety induce an increase in the degree of risk aversion. I find that the implied volatility, as reflected through VIX and VXO, significantly increases on the day of the event, which may imply that the Ebola outbreak events also affect investors' perceived risk. In addition, I observe persistence of the effect on the first day following the event day whereas I observe no return to the prevailing average value before the event. This result provides evidence that fear and anxiety, rather than rational behavior, affect investor decisions in the context of the Ebola outbreak.

Furthermore, I observe the relationship between the mass media and communication of risks. My research confirms findings from the past research that high-consequence and low-probability events, such as the Ebola outbreak events, are overemphasized in the media and create sentiment effects. I find that the event effect is stronger for securities that are exposed to the intense media coverage compared to securities less covered in the media.

I can conclude that the media-driven pessimism and optimism—induced by the Ebola outbreak events—can significantly influence investors' decision-making process when investing in companies of different capitalization size and industry of operation.

2 Social Media and Political Power: The Impact on the Financial Markets♣

2.1 Overview

I evaluate President Trump's political power on the financial markets through his social media statements around the 2016 U.S. presidential elections. My results show that in his public statements Trump is more likely to cover the companies close to his knowledge, companies with which he had an established business and political connection, large companies, and companies with presence on the international markets. Additionally, the event-study analysis finds evidence that Trump can affect companies' stock outcomes, trading volume, and stock price volatility through tweeting and appearance in the news. Finally, Trump's statements carrying a negative linguistic tone result in negative returns for the mentioned companies.

2.2 Introduction

Social media is a modern phenomenon whose impact is yet to be fully understood, especially when used by people with political power. In the past decade, world leaders have leveraged the power of the social media to connect with their constituents. One of the most notable users of social media is the 45th President of the U.S., Donald J. Trump, who has used it in an unprecedented manner during his election campaign and since taking office. Besides making political statements and announcing actions and policies, Trump uses social media to attack, pressure, and complimenting specific firms. For example, his tweet "Boeing is building a brand new 747 Air Force One for future presidents, but costs are out of control, more than $4 billion. Cancel order!" received 141,634 likes, was retweeted 42,984 times and was circulated as news in many media outlets, including the Chicago Tribune and Reuters. As a consequence, Boeing's share price dropped by 1.6%. A month later, on Jan 4, 2017, when Trump praised Ford Motor Company for scrapping a new plant in Mexico and creating 700 new jobs in the U.S., Ford's share price increased by almost a dollar (from $11.76 to $12.66), and when Trump praised Fiat Chrysler Automobiles NV for its plans to add 2,000 U.S. jobs, its share price increased by 2.4%.

Historically, past presidents have utilized different channel of communication to express their views or to make public statements. For example, Franklin D. Roosevelt used radio, John F. Kennedy used television, and Barack Obama used the internet (including social media). Compared to past presidents, Trump's communications are more frequent, more specifically targeted, often more belligerent, and have a wider reach. By May 2017, his social media

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audience was over 45 million Americans. Trump's use of social media allows him to instantaneously communicate his messages to a large audience in the U.S. and globally.

The increasing use of social media by political leaders raise the question of whether and how this new form of communication translates into political influence. To address this question, I investigate the impact of Trump's statements on the shareholder wealth, share price volatility, and trading volumes of targeted firms. I hand collect Trump statements—his tweets and news media statements—that target public firms. I obtain Trump tweets from the official Trump Twitter archive by filtering out the time-nonoverlapping tweets in which Trump explicitly mentions a U.S. listed company on either NYSE or Nasdaq in his presidential elections rhetoric. I obtain the media circulated statements by browsing the three largest U.S. newspapers by circulation using the LexisNexis business news and article search engine. To retrieve Trump's statements from the LexisNexis, I use the search term "Trump 2016 elections and U.S. companies". During the period from June 2015 to June 2017, there are 134 statements - consider to be the event days i.e. events - from 111 affected firms.

Trump's statements of pronouncements and denouncements about companies that he thinks deserve his praise or ire may in fact have a long-term effect. As the president of the U.S., Trump has the power to implement economic policies that could affect a firm's cash flow, provide financial support, and help companies in securing government contracts. In addition, investors might react to social media statements because Trump's views about a company may change the firm's risk environment or may affect investor sentiments. The potential for tweets to be interpreted as relating to these consequential actions can influence the actions of investors. The impact that Trump media statements have on companies might be driven by the Trump's motive why the companies are mentioned in the first place.

First, I try to underpin how Trump selects the companies that he puts in spotlight through Twitter and media. I employ a logistic regression analysis to investigate factors driving the likelihood of a firm being twitted or news-broadcasted by Trump around the election period. I find evidence that Trump is more likely to cover the companies close to his knowledge, companies with which he had an established business connection, large companies, and companies with a presence on the international markets.

Second, I estimate the economic impact of Trump's statements on shareholders' wealth using two approaches. To quantify the impact of Trump's social media statements on the financial markets I conduct an event study analysis. I compute the daily cumulative abnormal returns (CAR) using the market (value-weighted) model over a 1-day window [0, 0]—where event day is zero—2-day window [0, 1], and 6-day window [0, 5]. I find that the CARs on the event days are negative for all three event windows (-0.114%, -0.400%, and 0.393% respectively) and statistically significant.

I classify the sample according to the linguistic tone of Trump's media statements. Over a 1-day window [0, 0], the negative posts have negative CAR of 0.184% whereas non-negative statements have positive CAR of 0.194%. In general, Trump posts on social media have an impact on shareholders' wealth but the effect in some tests is weak or insignificant. This might suggest that Trump's posts do not carry exquisite economic importance, but rather serve his image and justify economic policy.[14]

I divide the sample of statements into two groups relative to the time of the announcement of presidential election results on November 8th, 2016. The election of Donald Trump as the 45th President of the U.S. was not an expected outcome and it surprised most observers. I find that the effect from statements made after the Election Day is negative and more pronounced than before the Election Day. That is, the difference in CAR between two groups (CAR (after) - CAR (before)) is negative and significant. This is aligned with the view that investors took Trump posts more seriously after he gained political and socio-economic decision-making power.

To further explain the economic impact of Trump statements I conduct a cross-sectional regression analysis. I analyze the relationship between the CARs and Trump statement's characteristics and firm characteristics. I include the timing of the statement (i.e., whether it is before or after the 2016 presidential election), the tone of the statement on the social media (i.e., negative versus non-negative), and whether the mentioned firm belongs to the media industry. In addition to firm size, profitability, leverage, risk level, I also include other controls related to the political orientation of a firm and its political connection to Trump. Following Massoud and Zhou (2018), I classify firms based on the top management political orientation and companies' business connection to Trump.

I find that the political factors and companies' business connection to Trump are likely to influence companies' stocks, trading volume, and stock price volatility. The number of connection channels in which certain company is related to Trump, is positively related to the CAR [0,5], where each additional channel brings 0.278 percentage points higher CAR [0,5]. However, the relationship is insignificant for short term CARs and when I control for firm fixed effects. I also analyze the relationship between the abnormal trading volume (AV) and the number of connection channels. The relationship is negative and statistically significant. With each additional channel the abnormal trading volume drops for about 0.161 percentage point.

In the past decade, social media and specifically Twitter has gained popularity in the corporate world and studies have begun to show some of the impacts of a social media usage by firms. Jung et al. (2017) report that about 50% of the S&P 1,500 firms have created either a corporate Twitter account or a Facebook page, with a growing preference for Twitter. The current literature investigates two channels through which social media affects capital markets. The first channel focuses on social media statements initiated by the firm. For

[14] Daniel Dale – Washington Bureau Chief, Toronto Star Updated February 20, 2018: https://www.thestar.com/news/world/analysis/2018/02/20/two-days-23-false-claims-from-donald-trump-including-one-spectacular-lie.html

example, Lee et al. (2015) show that firms that interact with investors using Twitter or Facebook reduce information asymmetry among investors (see also Blankespoor et al., 2014). The second channel focuses on statements initiated by investors. For example, Bollen et al. (2011) investigate the relationship between overall stock market performance and investor mood derived from analyzing text content of Twitter. Curtis et al. (2014) examine the relationship between the intensity of Twitter activity and the sensitivity to earnings surprises. Bartov et al. (2018) examine whether information on Twitter can help predict a company's future earnings and stock returns. Overall, these studies show that social media statements by either firms or investors resolve information asymmetry and have a significant impact on stock prices and market liquidity.

One of the major concerns with the current social media studies is the credibility of the information on some statements. This is because participation on social media is not monitored, i.e. anyone can set up a Twitter account and tweet anonymously about any stock. Accordingly, information on Twitter can be intentionally or unintentionally misleading and thus of limited usefulness for conducting a valuable analysis. One of the notable contributions of this chapter is to overcome this limitation by studying social media statements initiated by an influential political leader. In June 2017, former White House Press Secretary Sean Spicer said during his tenure that Trump's tweets are "considered official statements by the President of the United States".[15]

This chapter makes the following contributions. To the extent of my knowledge, this study is among the first to fully focus on overcoming the limited credibility of social media information by studying social media statements initiated by a credible-enough source, influential political leader.

Relating to the literature analyzing the relation between the U.S. Presidents' politics and U.S. the economy and financial markets, this chapter is closely related to Wagner et al. (2017) who observe expectations to realizations of President Trump's pre-election day political agenda and its post-election day effects. They find evidence that the financial markets reflect investor expectations on economic growth, taxes, and trade policies. From investors' perspective, recent studies show that investors change their portfolio compositions (Addoum and Kumar, 2016), companies reduce their capital investments (Julio and Yook, 2012), and stock market volatility is higher (Boutchkova et al., 2012) before national elections. Consistent with the findings mentioned above, my results suggest that the stock market is sensitive to political news since even presidential candidates who may not be in power yet influence stock returns, trading volume, and stock price volatility.

Regarding the literature analyzing specifically President Trump's standalone actions, this study is related to Huang and Low (2017) who simulate Donald J. Trump's communication

[15] Elizabeth Landers, CNN Updated June 6, 2017: http://edition.cnn.com/2017/06/06/politics/trump-tweets-official-statements/index.html

style, appearance and personal gestures through a Battle of the Sexes game. In both mine as well as their study, the results point to the presence of an unprecedented and unique communication style, where I further put the accent on Trump's aggressive rhetoric towards the financial markets. Within similar lines, my study is related to Chen et al. (2016) and shows that negative linguistic tone of political speeches predicts negative stock returns.

Regarding the literature analyzing connections between politicians and company executives, this study contributes with evidence consistent with Acemoglu et al. (2016) and suggests that at least in the minds of investors, connections between politicians and companies' top management can be of great importance for the companies.

Lastly, relating to the strand of literature that examines the effect of investor sentiment on the financial markets, this chapter's contributions are closely related to Kaplanski and Levy (2010b) who show that certain events (e.g., aviation disasters) tend to generate negative sentiment within two days after the event. Along those lines, this chapter sheds new light on the role of the presidential signaling and information dissemination to the financial markets, and their psychological effects on investors' decision-making process. The results provide evidence that there is a relationship between Trump's statements and investors' actions upon those statements.

The remainder of the chapter goes as follows. Section 2.3 reviews the related literature. Section 2.4 describes the data. Section 2.5 reveals the methodology and presents the hypotheses tested in this study. Section 2.6 presents the logit analysis results. Section 2.7 presents the event study results. Section 2.8 discusses robustness tests and Section 2.9 concludes the chapter.

2.3 Literature Review

This chapter is related to three strands of the existing literature. It relies on the observed relations between: companies' exposure to presidential candidate's notions and remarks in the social media, companies' political orientation and business connections to the presidential candidate, and investors' sentiment provoked by the presidential candidate's disseminated information.

The presidential candidates are present in the media for several months during their election campaigns. To shape the general opinion of the public in their favor with intentions to win the election, candidates constantly give political speeches and interact with the broad mass of voters (Bartels, 2006). Since the presidential candidates can influence the public opinion about the economy, they are also likely to be able to affect investor sentiment, and thus the asset prices (Holbrook, 1999). Some presidential public appearances may create either positive or negative sentiment that affects investors' investment decisions and, thus, the corresponding stock prices. Feldman et al. (2010) and Chen et al. (2016) find that political speeches that contain economic information increase aggregate market returns and trading volume but decrease market volatility. When examining the content of the speeches, they find that net positive linguistic tone increases market returns and trading volume whereas net negative linguistic tone has the opposite effect. Chen et al. (2016) conclude that the stock market is quite sensitive to political news since even politicians who may not yet be in power can influence stock prices, volatility and trading volume. In addition, Wagner et al. (2017) studied the reaction of company stock prices to Trump becoming a President of the United States. They find that companies and industries followed in a favorable tone by Trump outperformed the rest.

Bartov et al. (2018) focus specifically on observing the impact of social media on predicting returns. They test whether individuals' statements on Twitter just before a firm's earnings announcement predict its earnings and announcement returns. They find that the collective opinion from individual tweets successfully predicts a firm's future quarterly earnings and announcement returns. Their results hold for tweets that convey original information, as well as tweets that disseminate existing information, and are stronger for tweets providing information directly related to firm fundamentals and stock trading.

Blinder and Watson (2016) explore the U.S. economy performance with respect to the U.S. presidents dating back to President Truman, touching upon the investors' rational behavior aspect. One thing they look is what happens in the markets during the lame duck session between an election and the inauguration of the new president. They find that stock prices rise much faster under Democratic presidents than under Republican presidents.

Several studies examine the connection channels and political orientation of certain companies to government officials (see Massoud and Zhou, 2018; Acemoglu et al., 2016; Amore and Bennedsen, 2013). Acemoglu et al. (2016) results suggest that at least in the mind of the investors, connections to top executive officials can sometimes matter a great deal in the U.S., for example, during periods of presidential elections uncertainty or when there is a great deal of market turmoil. Akey and Lewellen (2017) find evidence supporting the notion that political connection and firm value are positively associated. This evidence is consistent with the "exchange of favor" hypothesis and the model proposed by Shleifer and Vishney (1994), in which politicians provide aid to companies in exchange for personal benefits (e.g., votes). Lastly, Amore and Bennedsen (2013) find connections of various kinds exist everywhere, even in relatively uncorrupt Denmark where family connections to politicians are unlikely.

2.4 Data

2.4.1 Trump's Public Statements

The data examined cover Twitter as well as mass-media circulated statements in the period from June 2015 to June 2017 (a total of 449 trading days) in which a U.S. publicly listed company is explicitly mentioned by Donald J. Trump. The entire period incorporates 134 statements which I consider to be the event days i.e. *events*. The Twitter statements are obtained from the official Trump Twitter archive[16] by manually filtering out each tweet in which Trump explicitly mentions a U.S. publicly listed company on either NYSE or Nasdaq in his presidential elections rhetoric (see, Table B.2). The media circulated statements are obtained from the LexisNexis business news and article search engine. To retrieve Trump's statements from the LexisNexis, the search term "Trump 2016 elections and U.S. companies" has been used. In addition, I browse the three largest U.S. newspapers by circulation (The New York Times, Chicago Tribune and The Wall Street Journal) [17] reporting on the events and companies of interest.

Both sources from which the statements are collected are to some extent daily or weekly direct updates by Trump and include, for example, news about future intentions and plans in the political as well as socio-economic environment in the USA. Regularly spaced updates may be anticipated by the financial investors and thus priced preceding the actual update. For this reason, the sample of statements considers only those updates documenting a news-event for a first time, i.e. a first-time statement about a certain company or group of companies, first-time announcement on realized actions etc. A strategy of this type helps to ensure the independence of sequential statements, since transmission of information on the social networks occurs somewhat unpredictably.

2.4.2 Identifying the Linguistic Tone of Trump's Public Statements

To identify the linguistic tone of Trump's statements, I manually conduct a textual analysis and I form two linguistic tone categories: negative and non-negative. I follow Loughran and McDonald (2011) dictionary (LM) and Harvard-IV-4[18] that can identify text tone in several contexts. Harvard-IV-4 list can identify the text tone in sociology and psychology-oriented topics, whereas the LM dictionary can better reflect the linguistic tone of economic texts because it more efficiently minimizes the misclassification of words with economic meaning. The linguistic tone analysis results in 87 negative and 47 non-negative statements.[19] All statements are summarized in detail in Table B.2 and Table B.4.

2.4.3 Trump's Business Connections and Political Donation Data

I use muckety.com[20] relationship maps to construct Trump's business-connections network. These maps show the links between an individual to other people or organizations. Muckety.com's advantage over other data providers is that it is not user-contributed, and it

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[16] http://www.trumptwitterarchive.com/#/archive/account/realdonaldtrump
[17] Considers both printed and online subscription coverage on a national level.
https://www.statista.com/statistics/184682/us-daily-newspapers-by-circulation/
[18] Harvard-IV-4 online access at: http://www.wjh.harvard.edu/~inquirer/homecat.htm
[19] If a tweet mentions more than one company, the tweet is examined to capture the impact on each company. This is important especially in the case when a tweet is of non-negative linguistic tone for one of the companies and negative for another one.
[20] Muckety.com is an award-winning ("Outstanding Use of Digital Technologies" award) website that uses interactive maps to show relationships between people, businesses and organizations. The maps focus on actual relationships and not mere connections.

focuses on the links of influence encompassing government, non-profit, and business affiliations.

For the period around the 2016 U.S. presidential elections, I gathered data on the active business links of Trump. A company is considered as having connection to Trump if it has direct business relations with any of Trump's businesses or if any of its CEOs, board members or treasurers has relation to him and his family. Some well-known connections between Trump and the private sector include his ties to Bank of NY Mellon, Goldman Sachs, BlackRock etc.

I create two variables referring to Trump's connections. The first is a dummy variable, "Connect", which equals one if a firm is classified as being connected to Trump and zero otherwise. The second counts the number of connection channels through which each firm is connected to Trump and it is denoted as "Connection channels no."

Using the same connection identification procedure as above, I further extend the sample of companies to their most related competitors within the industry they operate in. To correctly match each company with its most related competitors, I use the Dun & Bradstreet's Hoovers database. Hoovers database automatically provides each company's top three competitors based on their gross revenue, net profit margin, and net operating cash flows. At the end, I manually match each firm's competitor to Trump if a business connection exists.

I gathered the political donation data from the U.S. Federal Election Commission (FEC) database. FEC provides transaction-level data categorized by election cycle. I use two sources of donations. First, I consider the general elections for the House of Representatives and the Senate and I restrict the sample to the donations made during the election period—in my sample from June 2015 to June 2017. Second, I consider direct donations to Trump's 2016 election campaign. It is required, by law, donors to U.S. federal election campaigns to report detailed information related to their employment and position they have within the company they work for. Hence, I match the donation data to the company sample to later be ready for examination. In addition, I create two sets of variables to observe the House and Senate campaign donations. The first is the "CEO Republican" and "CEO Democrat", which are dummy variables equal to one if the firm's top management have donated to either the Republican or Democrat party, and the second is "CEO donation to Trump," which is a dummy variable equal to one if a firm's central figures have specifically donated to Trump's campaign.

2.4.4 Stock Market Data

To test whether Trump's public statements have a direct effect on the stock returns of the companies that he mentions in the realm of the 2016 U.S. presidential elections, I employ the value-weighted rates of return (see Table B.1 for definition) from the Center for Research in

Security Prices (CRSP) of the New York Stock Exchange (NYSE) and Nasdaq Composite listed companies. In addition, I use the S&P500 index as a market performance benchmark. The NYSE Composite primarily contains large stocks generally characterized by good information dissemination, whereas the Nasdaq Composite primarily includes some of the major tech stocks. I further use the Bloomberg database to build the portfolios of companies which are listed on the U.S. stock markets (NYSE and Nasdaq) and are *explicitly* mentioned by Trump. To ensure unbiased selection and categorization of the companies I use the following four-step procedure.[21] Firstly, I select the companies by status—I am interested in only the publicly listed companies mentioned in Trump's statements. Second, I further select the companies that have a domicile in the U.S. Third, I set up the period of operation of the companies from June 2015 to June 2017. Fourth, I manually filter the companies resulted from the previous three steps to match the event days' list of announcements by Trump. At the end, the sample consists of 111 companies listed on NYSE and Nasdaq Composite that were directly involved in Trump's public statements. Table B.3 summarizes the company stocks filtered by the above procedure.

I gathered accounting data from Compustat, Thomson Reuters Datastream, and the industry classification from Ken French's website. To control for firm characteristics like size I include leverage, profitability, marginal tax rate, Altman z-score, and internationalization status for each firm for the period from June 2015 to June 2017. "Size" is reported as logarithm of total assets, "Profitability" is return on assets, "Leverage" is the ratio of total debt to total capital, "Altman z-score" represents company's likelihood of bankruptcy, "Marginal tax rate" is the amount of tax paid on an additional dollar of income and "International" is measured as the change of foreign assets as a % of total assets (Wagner et al., 2017).

I also add "Media-excluding" variable, which equals zero if the company belongs to the media industry and one otherwise, to control for the media industry bias in my sample. Potentially, Trump statements have different effect if the media company is mentioned. Detailed definitions of all variables are presented in Table B.1.

2.5 Methodology and hypotheses

I first use logit analysis to determine the key factors describing the likelihood of a firm being mentioned by Trump. I run the following logistic regression:

$$y_i = c + \gamma_1 \cdot Z_i + \gamma_2 \cdot M_i + \gamma_3 \cdot controls_i + \epsilon_t, \tag{1}$$

where the dependent variable y_i is a dummy variable equal to one if a firm is explicitly mentioned by Trump statements and zero otherwise. In addition, I expand on several specifications regarding the linguistic tone of the statements. First, I denote by y_i a dummy

[21]The four-step selection procedure is an automated filter available in both Bloomberg and Orbis databases software.

variable equal one if the firm is mentioned by Trump statements in a negative linguistic tone and zero otherwise. Second, I denote by y_i a dummy variable equal one if the firm is mentioned by Trump statements in a non-negative linguistic tone and zero otherwise. Z_i is the set of variables for firms' business connections to Trump to which I add firm's competitors' connections to Trump as defined in the data section. M_i is the set of variables for political connections and campaign donations from firm's i top management. $Controls_i$ represents the set of control variables for firms' size, leverage, profitability, Altman z-score, marginal tax rate, media-excluding companies, and firm's international presence. Control variables are included to investigate basic firm characteristics that could have some effect on the observed relation between linguistic tone, political and business connectedness, and being mentioned by Trump (see, e.g. Santa-Clara and Valkanov, 2003; Acemoglu et al., 2016; Massoud and Zhou 2018). Following Petersen (2006), I exercise the logit analysis with adjusted standard errors for the impact of industry-level clustering and for each variable in the model I compute its elasticity[22] (economic importance). In addition, the logit analysis is repeated including industry fixed effects (FF 30-Industry classification) to ensure that my results are not driven by any specific sector(s).

I further employ an event-study methodology to evaluate the impact of Trump's statements on the stock returns, trading volume, and stock price volatility of the companies that he mentions. I employ the one-factor market model, as inspired by prior research (see, e.g. Peress, 2014; Acemoglu et al., 2016). The one-factor model is estimated as:

$$r_{i,t} = \alpha_0 + \beta_1 r_{m,t} + \varepsilon_t \qquad (2)$$

where $r_{i,t}$ is the rate of return on stock i in period t and $r_{m,t}$ is the S&P500 rate of return, which serves as proxy for the market portfolio.

I begin the analysis by computing the cumulative average abnormal returns (CARs) around the statements considered. The abnormal returns (ARs) are defined as the difference between the actual rate of return of the stock considered and its ex-post expected rate of return over the whole length of the event window. I position 250 trading days in the estimation period ending 30 days prior to the statement day, i.e. day 0, and I estimate three event windows: [0, 5], [0, 0], and [0, 1] (for more on event study designs, see MacKinlay, 1997).

The statements I observe are temporally clustered. Hence, the event study would suffer from overlapping windows if all events were considered. I use one of the two selection criteria to select the statements. The first selection criterion is labelled as the *last occurrence* and chooses a statement only if it is not followed by another statement within 7 days after its occurrence. The second selection criterion is labelled as the *first occurrence* and selects statements in chronological order (sequence). It starts with the first statement in the sample,

[22] Elasticity is calculated as d(ln F)/d(ln x), where d is the first derivative, ln (F) is the natural logarithm of the density function and ln (x) is the natural logarithm of the explanatory variable and is evaluated at the sample means of the explanatory variables.

ignores all statements showing up in the following 7 days, takes the next statement in succession, ignores the following 7 days, and so on until the whole sample is exhausted. In a more illustrative way, assume there are five statements taking place on dates d_0, d_1, d_2, d_3, and d_4 where d_1, d_2, and d_3 are temporally clustered. The *last occurrence* uses statements for CAR calculation taking place on days d_0, d_3, and d_4 and the *first occurrence* chooses d_0, d_1, and d_4. With this strategy, I filter out 45 Trump statements having overlapping event windows.

To observe whether the statements affect the stock returns, trading volume, and stock price volatility of the companies that Trump mentions, I run the following regression model (following, e.g., Acemoglu et al., 2016):

$$y_i = c + \gamma_1 \cdot X_i + \gamma_2 \cdot Z_i + \gamma_3 \cdot M_i + \gamma_4 \cdot controls_i + \epsilon_t \tag{3}$$

where y_i is either one of the cumulative average abnormal returns CAR [0, 5], CAR [0, 0], and CAR [0, 1], the abnormal trading volume (AV) calculated as in Joseph et al. (2011):

$$AV_{i,t} = (V_{i,t} - V_{avg,t})/V_{avg,t} \text{ where } V_{avg,t} = \frac{\sum_1^j V_{i,t-j}}{J};\ J = 7 \text{ previous trading days} \tag{4}$$

or the Rogers and Satchell (1991) range-based estimator of stock prices' volatility which is calculated as:

$$\hat{\sigma}_{it}{}^2 = (H_{it} - C_{it})(H_{it} - O_{it}) + (L_{it} - C_{it})(L_{it} - O_{it}), \tag{5}$$

where O_{it}, C_{it}, H_{it} and L_{it} are the natural log of the opening, closing, high, and low prices for company i on day t, respectively. X_i is measuring whether the linguistic tone of the statements predicts stock market returns thus also affects the trading volume and stock price volatility (see, e.g. Tetlock, 2007; Chen et al., 2016). Z_i is a measure of business connections to Trump and M_i is the political connections and campaign donations from firm *i's* top management. $Controls_i$ represents the set of control variables for firm size, leverage, profitability, Altman z-score, and a dummy variable denoting media-excluding company. Lastly, the regression analysis is also repeated with industry fixed effects as controls.

The following hypotheses are tested in this chapter. First, I investigate factors describing the likelihood of a firm being mentioned by Trump in the period from June 2015 to June 2017. Following the analogy of Wagner et al. (2017) and Massoud and Zhou (2018) I would expect Trump to be inclined towards mentioning companies with which he had an established business connection, companies of high importance for the U.S. society from both economic and policy perspective, and companies with the presence on the international markets.

Second, I hypothesize that the linguistic tone used in Trump's statements predicts stock market returns, affects the trading volume, and the stock price volatility. This hypothesis is supported by the previous research suggesting that presidential candidates often attempt to target certain entities (voters, companies, institutions etc.) by using negative tone when criticizing in the public (Lau and Pomper, 2002). Recent studies in the finance literature show that the linguistic tone in the media, conference calls, and corporate fillings affects investor sentiment and thus, stock returns (Tetlock, 2007; Druz, Wagner and Zeckhauser, 2016).

Third, I hypothesize that the political factors such as donations to certain party and companies' business connection to the presidential candidate are likely to influence companies' stocks. Santa-Clara and Valkanov (2003) find that presidential candidates' relation to a certain political party is reflected in return premiums due to the business sector expectations regarding the potential winner of the election. Hong and Kostovetsky (2012) conclude that it is possible that investors with political preferences pay more attention to political rhetoric and react more when the presidential candidate of their favored political party gives a speech. In these circumstances, the stock returns of a Republican (Democratic) company would be more sensitive to the political rhetoric of Republicans (Democrats).

2.6 Logit Analysis

2.6.1 Descriptive statistics

Table 2.1 reports descriptive statistics for the linguistic tone in which a company is covered in Trump statements, company's business and political connection to Trump, company's competitor connection to Trump, firm financial and donation data. I record a total number of 446 observations from my sample of Standard & Poor's Index companies in the period from June 2015 to June 2017. A company is considered to be covered by Trump statements if it is explicitly mentioned in Trump's public statements. Panel 1 of Table 2.1 presents descriptive statistics on the full sample of companies. Panel 2 of Table 2.1 subsamples the companies covered by Trump statements. For example, 42.8% of the observations represent companies covered by Trump statements that are not operating in the media sector. This means that more than half of the observations in this subsample record media companies. Furthermore, in 48% and in 46.2% of the observations a company and a company's competitor are connected to Trump, respectively. Panel 3 of Table 2.1 presents descriptive statistics on the companies not covered by Trump statements. In this subsample, a company's top management is politically inclined towards the Republicans in 26.6% of the observations. In addition, in 20.5% of the observations a company's competitor was twitted by Trump.

Panel 4 of Table 2.1 presents difference in means statistics between the companies covered by Trump and the companies not covered by Trump statements. One, two, and three asterisks indicate a significance level of 10%, 5%, and 1%, respectively. I observe that the difference in means between the two groups of variables is statistically significant on at least 10% significance level. Assuming a null-hypothesis that the difference in means between the two groups is zero, the coefficients indicate that I can reject the null-hypothesis and conclude that there is a statistically significant difference in means between the two groups of variables.

Table 2.1 Descriptive statistics (Logit Analysis)

The table reports descriptive statistics for the linguistic tone in which a company is covered in Trump statements, company's business and political connection to Trump, a company's competitor connection to Trump, firm financial and donation data. I record a total number of 446 observations from my sample of Standard & Poor's Index firms in the period from June 2015 to June 2017. A company is considered to be covered by Trump statements if it was explicitly mentioned in Trump's public statements. Panel 1 presents descriptive statistics on the full sample of companies. Panel 2 subsamples the companies covered by Trump statements. Panel 3 presents descriptive statistics on the companies not covered by Trump statements. Panel 4 presents difference in means statistics between companies covered by Trump and the companies not covered by Trump statements. One, two, and three asterisks indicate a significance level of 10%, 5%, and 1%, respectively. Detailed description of the variables can be found in Table B.1.

	Mean	Min	p1	p25	p50	p75	p99	Max	St. dev.	Obs.
Panel 1. Full Sample										446
Media excluding	0.944	0	0	1	1	1	1	1	0.229	446
Negative	0.450	0	0	0	0	1	1	1	0.594	446
Non-Negative	0.299	0	0	0	0	0	1	1	0.432	446
CEO Republican	0.258	0	0	0	0	0	1	1	0.234	446
Connect	0.213	0	0	0	0	0	1	1	0.338	446
No. of conn. to Trump.	0.151	0	0	0	0	0	2	3	0.416	446
Competitor connection to Trump	0.127	0	0	0	0	0	1	1	0.333	446
Competitors tweeted	0.053	0	0	0	0	0	1	1	0.225	446
Size	310.670	3.840	17.021	73.792	162.381	381.241	244.640	402.670	44.360	446
Profitability	0.088	-1.375	-0.646	0.049	0.092	0.141	0.333	0.831	0.150	446
Leverage	0.450	0	0	0.129	0.370	0.548	1.396	18.926	1.063	446
Altman z-score	3.320	-7.845	-1.607	1.291	2.805	4.282	19.575	35.956	3.554	446
Marginal tax rate	0.097	-0.319	-0.050	0	0.005	0.043	0.700	22.61	1.079	446
International	0.716	0	0	0	1	1	1	1	0.451	446
CEO donation to Trump	0.285	0	0	0	0	1	1	1	0.452	446
Panel 2. Companies covered by Trump statements										
Media excluding	0.428	0	0	1	1	1	1	1	0.238	95
Negative	0.626	0	0	0	1	1	1	1	0.487	95
Non-Negative	0.374	0	0	0	0	1	1	1	0.373	95
CEO Republican	0.129	0	0	0	0	0	1	1	0.122	95
Connect	0.480	0	0	0	0	0	1	1	0.409	95
No. of conn. to Trump.	0.238	0	0	0	0	0	2	2	0.495	95
Competitor connection to Trump	0.462	0	0	0	0	1	1	1	0.502	95
Competitors tweeted	0.795	0	0	0	0	0	1	1	0.238	95
Size	50.959	2.128	2.128	9.639	21.713	65.444	402.672	402.672	69.563	95
Profitability	0.122	-0.054	-0.054	0.072	0.102	0.159	0.429	0.429	0.084	95
Leverage	0.740	0	0	0.312	0.453	0.607	18.926	18.926	2.267	95
Altman z-score	3.643	0	0	2.062	3.201	4.905	12.255	12.255	2.308	95
Marginal tax rate	0.415	-0.094	-0.094	0	0.015	0.063	22.615	22.615	2.773	95
International	0.850	0	0	1	1	1	1	1	0.359	95
CEO donation to Trump	0.313	0	0	0	0	1	1	1	0.467	95
Panel 3. Companies not covered by Trump statements										
Media excluding	0.955	0	0	1	1	1	1	1	0.206	351
Negative	0	0	0	0	0	0	0	0	0	0
Non-Negative	0	0	0	0	0	0	0	0	0	0
CEO Republican	0.266	0	0	0	0	0	1	1	0.249	351
Connect	0.188	0	0	0	0	0	1	1	0.284	351
No. of conn. to Trump.	0.099	0	0	0	0	0	1	1	0.343	351
Competitor connection to Trump	0.124	0	0	0	0	0	1	1	0.156	351
Competitors tweeted	0.205	0	0	0	0	0	1	1	0.179	351
Size	24.642	3.847	1.474	6.900	15.265	31.997	122.973	266.103	29.437	351
Profitability	0.080	-1.375	-0.715	0.045	0.084	0.141	0.333	0.831	0.162	351
Leverage	0.398	0	0	0.002	0.351	0.538	1.396	11.337	0.661	351
Altman z-score	3.151	-7.845	-2.525	1.129	2.646	4.209	19.575	22.947	3.339	351
Marginal tax rate	0.041	-0.319	-0.050	0	0.004	0.043	0.616	1.586	0.120	351
International	0.689	0	0	0	0	1	1	1	0.463	351
CEO donation to Trump	0.260	0	0	0	0	1	1	1	0.439	351

Panel 4. T-test means comparison (companies covered versus not covered companies by Trump statements)

	Mean	t-stat	Combined Obs.
Media excluding	-0.527***	-3.203	446
Negative	0.626***	24.656	446
Non-Negative	0.374***	18.718	446
CEO Republican	-0.137*	-1.654	446
Connect	0.292***	2.942	446
No. of conn. to Trump.	0.139***	2.819	446
Competitor connection to Trump	0.338***	13.468	446
Competitors tweeted	0.590***	5.961	446
Size	26.317***	5.139	446
Profitability	0.041**	2.030	446
Leverage	0.342***	2.377	446
Altman z-score	0.492**	2.155	446

Marginal tax rate	0.373**	2.558	446
International	0.161***	2.697	446
CEO donation to Trump	0.053**	1.994	446

2.6.2 Logistic Regression Results: All Trump Statements

In this subsection I observe factors describing the likelihood of a firm being mentioned by Trump around the election period. Inspired from Trump's personal Twitter statements-such as: "Thank you to Ford for scrapping a new plant in Mexico and creating 700 new jobs in the U.S. This is just the beginning - much more to follow", I would expect Trump to be inclined towards mentioning the companies with which he had an established business connection and companies of high importance for his presidential election agenda from both economic and policy perspective.

Table 2.2 and Table 2.2.1 present the results from the logit analysis together with the elasticity (economic importance) for Trump's statements being a dummy variable equal to one if a firm is explicitly mentioned by Trump statements and zero otherwise. In addition, Table 2.2.1 present the estimates with industry fixed effects. Following Petersen (2006), I estimate all models using adjusted standard errors for the impact of industry-level clustering (using Fama-French 30-industry classification). To avoid collinearity between explanatory variables, not all variables are included in the models simultaneously.

Results in columns 1 to 9 of Table 2.2 and Table 2.2.1 comply with the expectations - that Trump is more likely to mention in his statements the U.S. companies of larger size, firms that pay more taxes than an average firm, and firms which their portion of foreign assets and intentions to invest abroad matter greatly for the U.S. economy. For example, in column 1 of Table 2.2, a 1% increase in firm's portion of foreign assets translates to 0.656% higher probability to be covered by Trump statements.

Furthermore, Trump is more likely to make statements about a company and a company's competitor to which he has an established business connection. The number of firm's connection channels to Trump, donations by company's top management to his campaign, and Trump's connection to specific company's main competitors positively contribute to the probability of appearing in Trump's public statements too. For instance, the "number of connection channels to Trump" points to the fact that with each additional channel of connection the likelihood of appearing in his rhetoric increases by 0.072% (column 6 of Table 2.2). Similarly goes when company's competitor is connected to Trump. With each additional connection to a competitor the probability of being mentioned increase by 0.168% (column 7 of Table 2.2).

Table 2.2 Logistic regression results from Trump's statements

The table reports coefficient estimates of logistic regression where the dependent variable is a dummy equal to one if a firm is explicitly mentioned by Trump statements and zero otherwise in the period from June 2015 to June 2017. Elasticity is calculated as d(ln F)/d(ln x), where d is the first derivative, ln (F) is the natural logarithm of the density function and ln (x) is the natural logarithm of the explanatory variable and is evaluated at the sample means of the explanatory variables. In addition to the control variables which include company size (log of total assets), leverage (total debt to total capital), profitability (return on assets), Altman z-score (likelihood of bankruptcy), marginal tax rate (the amount of tax paid on an additional dollar of income) and media excluding (control for non-media company effect), I control for company internationalization (change of foreign assets as a % of total assets in the tweeting period), CEO donation to Trump (whether firm's top management donates to Trump), CEO Republican (dummy variable equal to one if firm's top management is inclined towards the Republicans party, and zero otherwise), firm's connection to Trump, firm's competitor connection to Trump, competitor tweeted (equals one if firm's competitor is tweeted by Trump and zero otherwise) and firm's number of connection channels to Trump. One, two, and three asterisks indicate a significance level of 10%, 5%, and 1%, respectively.

	Dependent variable is all statements																	
	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)		(9)	
	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.
Size	2.684***	9.452***	2.625***	9.242***	2.677***	9.426***	2.306***	8.120***	3.445***	12.129***	2.355***	8.294***	3.845***	13.540**	3.832**	3.494**	2.750***	9.685**
	(6.68)	(6.79)	(6.41)	(6.52)	(6.60)	(6.70)	(5.62)	(5.65)	(5.37)	(5.42)	(5.67)	(5.70)	(5.78)	(5.84)	(5.83)	(1.97)	(6.56)	(6.64)
Lever.	0.000	0.000	-0.009	-0.003	0.001	0.000	-0.002	-0.000	-0.328	-0.126	-0.008	-0.003	-0.305	-0.117	-0.482	-0.185	-0.004	-0.001
	(0.001)	(0.00)	(-0.11)	(-0.11)	(0.01)	(0.01)	(-0.03)	(-0.03)	(-0.84)	(-0.83)	(-0.10)	(-0.10)	(-0.97)	(-0.96)	(-0.63)	(-0.62)	(-0.05)	(-0.05)
Profit.	4.456**	0.314**	4.550**	0.321**	4.393**	0.310**	3.931**	0.277**	2.835	0.200	4.070**	0.287**	3.208	0.226	4.188*	0.295*	4.920**	0.347**
	(2.23)	(2.29)	(2.32)	(2.38)	(2.20)	(2.25)	(1.98)	(2.03)	(1.04)	(1.06)	(2.07)	(2.12)	(1.23)	(1.26)	(1.66)	(1.69)	(2.46)	(2.52)
Altman z-score	0.124***	0.329***	0.124***	0.327***	0.123**	0.325***	0.126***	0.334***	0.191***	0.505***	0.119***	0.316***	0.197***	0.522**	0.195***	0.516**	0.126***	0.334**
	(2.61)	(2.71)	(2.61)	(2.70)	(2.57)	(2.66)	(2.80)	(2.90)	(3.53)	(3.56)	(2.69)	(2.79)	(3.49)	(3.54)	(3.42)	(2.47)	(2.59)	(2.67)
Marg. Tax rate	1.381***	0.047***	1.374***	0.047***	1.363***	0.046***	1.361***	0.046***	0.679	0.023	1.366***	0.046***	0.751	0.025	1.022	0.035*	1.535***	0.052**
	(5.98)	(6.71)	(5.65)	(6.34)	(5.62)	(6.26)	(6.34)	(7.04)	(1.50)	(1.53)	(6.37)	(7.06)	(1.33)	(1.36)	(1.53)	(1.56)	(6.18)	(6.83)
Media excl.	-0.823*	-0.665*	-0.808*	-0.653*	-0.803*	-0.650*	-0.452	-0.366	1.122	0.907	-0.393	-0.318	0.894	0.723	1.179	0.954	-0.473	-0.382
	(-1.78)	(-1.75)	(-1.73)	(-1.70)	(-1.74)	(-1.71)	(-0.89)	(-0.89)	(1.29)	(1.30)	(-0.73)	(-0.72)	(1.20)	(1.21)	(1.48)	(1.49)	(-1.06)	(-1.05)
Internat.	1.122**	0.656**	1.111**	0.650**	1.126**	0.658**	0.973*	0.569*	2.038***	1.192***	1.002*	0.586*	2.067***	1.209**	1.958***	1.145**	1.081**	0.632**
	(2.12)	(2.15)	(2.10)	(2.12)	(2.12)	(2.15)	(1.86)	(1.88)	(4.37)	(4.55)	(1.88)	(1.90)	(4.23)	(4.42)	(4.18)	(2.35)	(2.19)	(2.22)
CEO don. to Trump			0.247	0.054														
			(1.58)	(0.80)														
CEO Repub.					0.359	0.019												
					(0.55)	(0.54)												
Connect							1.165***	0.083***	0.935**	0.067***								
							(3.15)	(4.26)	(2.52)	(2.77)								
No. of conn. to Trump											0.904***	0.072***						
											(2.74)	(3.67)						
Compet conn. to Trump									4.592***	0.164***			4.692***	0.168**	4.645***	0.166**		
									(8.20)	(7.28)			(7.94)	(7.15)	(8.02)	(2.44)		
Compet tweeted															2.226***	0.064**	2.307***	0.067**
															(3.54)	(2.28)	(3.42)	(6.15)
No. of obs.	446		446		446		446		446		446		446		446		446	
Pseudo R^2	0.238		0.239		0.240		0.261		0.533		0.260		0.524		0.543		0.272	
Fixed effect	No		No		No		No		No		No		No		No		No	

Table 2.2.1 Logistic regression fixed effects results from Trump's statements

The table reports coefficient estimates of logistic regression where the dependent variable is a dummy equal to one if a firm is explicitly mentioned by Trump statements and zero otherwise in the period from June 2015 to June 2017. Elasticity is calculated as d(ln F)/d(ln x), where d is the first derivative, ln (F) is the natural logarithm of the density function and ln (x) is the natural logarithm of the explanatory variable and is evaluated at the sample means of the explanatory variables. In addition to the control variables which include company size (log of total assets), leverage (total debt to total capital), profitability (return on assets), Altman z-score (likelihood of bankruptcy), marginal tax rate (the amount of tax paid on an additional dollar of income) and media excluding (control for non-media company effect), I control for company internationalization (change of foreign assets as a % of total assets in the tweeting period), CEO donation to Trump (whether firm's top management donates to Trump), CEO Republican (dummy variable equal to one if firm's top management is inclined towards the Republicans party, and zero otherwise), firm's connection to Trump, firm's competitor connection to Trump, competitor tweeted (equals one if firm's competitor is tweeted by Trump and zero otherwise) and firm's number of connection channels to Trump. One, two, and three asterisks indicate a significance level of 10%, 5%, and 1%, respectively.

	Dependent variable is all statements																	
	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)		(9)	
	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.
Size	3.205***	11.709***	3.139***	11.467***	3.201***	11.696***	2.828***	10.323***	8.030**	29.397**	2.871***	10.486***	8.108**	29.676**	7.188**	26.271**	3.179***	11.559***
	(5.74)	(5.59)	(5.56)	(5.42)	(5.74)	(5.60)	(4.79)	(4.69)	(2.26)	(2.22)	(4.92)	(4.82)	(2.26)	(2.22)	(2.49)	(2.45)	(5.77)	(5.65)
Lever.	-0.042	-0.016	-0.050	-0.020	-0.038	-0.015	-0.071	-0.028	-0.579	-0.229	-0.101	-0.040	-0.589	-0.233	-0.558	-0.220	-0.051	-0.020
	(-0.15)	(-0.14)	(-0.18)	(-0.18)	(-0.13)	(-0.13)	(-0.23)	(-0.23)	(-0.65)	(-0.65)	(-0.32)	(-0.32)	(-0.64)	(-0.64)	(-0.74)	(-0.74)	(-0.17)	(-0.17)
Profit.	3.754	0.281	3.881	0.291	3.644	0.273	3.247	0.243	4.230	0.315	3.426	0.257	4.321	0.322	5.784	0.429	4.325	0.322
	(1.35)	(1.38)	(1.40)	(1.43)	(1.31)	(1.34)	(1.16)	(1.18)	(0.71)	(0.71)	(1.21)	(1.23)	(0.72)	(0.72)	(1.00)	(1.01)	(1.55)	(1.59)
Altman z-score	0.136*	0.381*	0.135*	0.378*	0.133*	0.372*	0.137*	0.383*	0.375*	1.056*	0.130*	0.364*	0.374*	1.051*	0.323*	0.904*	0.136*	0.378*
	(1.86)	(1.90)	(1.85)	(1.89)	(1.81)	(1.85)	(1.84)	(1.89)	(1.82)	(1.79)	(1.73)	(1.76)	(1.78)	(1.75)	(1.85)	(1.84)	(1.83)	(1.86)
Marg. Tax rate	1.041	0.040	1.044	0.040	1.001	0.038	1.020	0.039	0.582	0.028	1.021	0.039	0.585	0.029	0.570	0.023	-1.151	0.044*
	(1.37)	(1.59)	(1.35)	(1.58)	(1.31)	(1.52)	(1.33)	(1.53)	(0.91)	(0.53)	(1.33)	(1.53)	(0.91)	(0.50)	(0.85)	(1.52)	(-1.49)	(1.77)
Media excl.	-0.993	-0.833	-0.982	-0.824	-0.957	-0.803	-0.569	-0.477	2.455	2.064	-0.522	-0.438	2.603	2.188	2.091	1.755	-0.587	-0.490
	(-1.32)	(-1.31)	(-1.31)	(-1.29)	(-1.27)	(-1.26)	(-0.71)	(-0.70)	(0.94)	(0.94)	(-0.64)	(-0.64)	(0.97)	(0.97)	(1.04)	(1.04)	(-0.75)	(0.75)
Interna.	1.080*	0.662**	1.079*	0.661**	1.081*	0.663*	0.944	0.578	4.278*	2.638*	0.978*	0.599*	4.370*	2.694*	3.489*	2.142*	1.000*	0.610*
	(1.94)	(1.96)	(1.94)	(1.97)	(1.93)	(1.95)	(1.61)	(1.62)	(1.85)	(1.85)	(1.66)	(1.67)	(1.83)	(1.82)	(1.85)	(1.85)	(1.83)	(1.86)
CEO don. to Trump			0.208	0.047														
			(1.63)	(0.55)														
CEO Repub.					0.632	-0.035												
					(0.67)	(-0.65)												
Connect							1.482***	0.108***	1.748	0.131								
							(2.80)	(3.59)	(1.27)	(1.39)								
No. of conn. to Trump											1.177***	0.095**						
											(2.73)	(3.52)						
Compet conn. to Trump									10.285**	0.356**			10.461**	0.362*	8.897***	0.293**		
									(2.50)	(1.96)			(2.48)	(1.94)	(2.67)	(2.43)		
Compet tweeted															3.406*	0.102**	2.764***	0.079***
															(1.87)	(2.13)	(3.23)	(5.69)
No. of obs.	446		446		446		446		446		446		446		446		446	
Pseudo R^2	0.220		0.261		0.190		0.232		0.542		0.220		0.390		0.396		0.241	
Fixed effect	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	

2.6.3 Logistic Regression Results: Negative and Non-Negative Linguistic Tone Statements

I find similar results when I separate Trump's statements by linguistic tone. Table 2.3 and Table 2.3.1 present the results together with the elasticity where the dummy variable equal to one is Trump's statements of negative linguistic tone and zero otherwise. Same as before, standard errors are clustered by industry using the Fama-French 30-industry classification and Table 2.3.1 presents the regression estimates including industry fixed effects.

Results in columns 1 to 9 follow similar pattern as the results in Table 2.2 and Table 2.2.1. To some point this is rather expected since 63% of Trump's statements in the sample contain a negative linguistic tone. The results suggest that the likelihood of a firm been mentioned by Trump depends on the size of the firm, profitability, marginal tax rate, and if the firm is present on the international markets. Furthermore, Trump appears to be inclined towards mentioning the firms to which he is connected to and for those firms' competitors. An interesting point to be noted here is that the magnitude of the estimates i.e. the economic importance is lower than when one takes all the statements without disentangling the linguistic tone. For example, in model 4 of Table 2.3 being connected to Trump translates to 0.073% higher probability to be negatively mentioned by him, whereas previously it was 0.083%. There are two potential explanations for the difference in magnitudes of the coefficients. First, having in mind that Trump is the only presidential candidate so far with a previous full-time role of a CEO, it might be that he is rather careful when assigning a negative linguistic tone to the companies he knows and is personally connected to. Second, bearing in mind that Trump is the first presidential candidate to use the social media as a primary tool for sharing information to the greater public, the population following his daily Twitter updates is smaller than the population following the regular news. The results point to the fact that the regular media transmitting routes are more likely to be used when covering firm's behavior, than revealing information for the same firm to the greater public via Twitter.

In Table 2.4 and Table 2.4.1 I present the results where the dependent variable is Trump's statements of non-negative linguistic tone. Different than previously, I find no statistically significant evidence for the likelihood of firms to appear in Trump's statements for firms with presence on the international markets. The donation as well as the political connection variables positively contribute to Trump's preferences when choosing which firms to pick up in his statements, however the estimates are statistically insignificant too. Firms' business connections and the number of connection channels to Trump once again appear to be statistically significant for the context of his public statements.

To sum up, the logistic regression results provide evidence for my hypothesis that Trump is more likely to cover the companies close to his knowledge, companies with which he had an established business connection, large companies, and companies with international presence.

Table 2.3 Logistic regression results from Trump's all statements of negative tone

The table reports coefficient estimates of logistic regression where the dependent variable is a dummy equal to one if a firm is explicitly mentioned by Trump statements in a negative linguistic tone, and zero otherwise, in the period from June 2015 to June 2017. Elasticity is calculated as d(ln F)/d(ln x), where d is the first derivative, ln (F) is the natural logarithm of the density function and ln (x) is the natural logarithm of the explanatory variable and is evaluated at the sample means of the explanatory variables. In addition to the control variables which include company size (log of total assets), leverage (total debt to total capital), profitability (return on assets), Altman z-score (likelihood of bankruptcy), marginal tax rate (the amount of tax paid on an additional dollar of income) and media excluding (control for non-media company effect), I control for company internationalization (change of foreign assets as a % of total assets in the tweeting period), CEO donation to Trump (whether firm's top management donates to Trump), CEO Republican (dummy variable equal to one if firm's top management is inclined towards the Republicans party, and zero otherwise), firm's connection to Trump, firm's competitor connection to Trump, competitor tweeted (equals one if firm's competitor is tweeted by Trump and zero otherwise) and firm's number of connection channels to Trump. One, two, and three asterisks indicate a significance level of 10%, 5%, and 1%, respectively.

	Dependent variable is all statements of negative tone																	
	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)		(9)	
	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.
Size	2.622***	9.603***	2.645***	9.688	2.613***	9.570***	2.313***	8.471***	2.668***	9.771***	2.427***	8.889***	2.912***	10.668***	2.901***	10.625***	2.647***	9.695***
	(5.41)	(5.64)	(5.53)	(5.76)	(5.37)	(5.59)	(5.01)	(5.17)	(4.31)	(4.44)	(5.22)	(5.40)	(4.35)	(4.50)	(4.18)	(4.31)	(5.24)	(5.42)
Lever.	-0.021	-0.008	-0.019	-0.007	-0.017	-0.006	-0.027	-0.010	-0.256	-0.101	-0.028	-0.011	-0.257	-0.102	-0.417	-0.165	-0.033	-0.013
	(-0.23)	(-0.23)	(-0.20)	(-0.20)	(-0.18)	(-0.18)	(-0.29)	(-0.29)	(-1.01)	(-1.00)	(-0.31)	(-0.31)	(-1.01)	(-1.00)	(-0.68)	(-0.68)	(-0.32)	(-0.32)
Profit.	6.566***	0.483***	6.533***	0.480***	6.421***	0.472***	6.025***	0.443***	6.021**	0.443**	6.258***	0.460***	6.386***	0.470***	7.266***	0.534***	7.343***	0.540***
	(3.54)	(3.71)	(3.55)	(3.72)	(3.43)	(3.58)	(3.30)	(3.46)	(2.41)	(2.51)	(3.44)	(3.60)	(2.59)	(2.69)	(3.14)	(3.25)	(3.97)	(4.17)
Altman z-score	0.064*	0.179*	0.065*	0.181*	0.062*	0.173*	0.070**	0.195**	0.051	0.142	0.064*	0.179*	0.047	0.132	0.034	0.096	0.043	0.120
	(1.81)	(1.84)	(1.91)	(1.94)	(1.76)	(1.79)	(2.10)	(2.15)	(1.21)	(1.21)	(1.90)	(1.94)	(1.00)	(1.01)	(0.53)	(0.53)	(0.93)	(0.94)
Marg. Tax rate	1.604***	0.056***	1.608***	0.056***	1.569***	0.055***	1.582***	0.055***	1.020***	0.036***	1.592***	0.056***	1.045***	0.036***	1.267***	0.044***	1.777***	0.062***
	(6.73)	(7.71)	(6.81)	(7.81)	(6.68)	(7.56)	(7.11)	(8.00)	(3.65)	(3.83)	(7.00)	(7.94)	(3.50)	(3.68)	(3.60)	(3.79)	(6.82)	(7.85)
Media excl.	-0.567	-0.473	-0.579	-0.484	-0.531	-0.444	-0.302	-0.252	1.010	0.844	-0.355	-0.297	0.807	0.674	1.295	1.083	-0.065	-0.054
	(-1.24)	(-1.23)	(-1.26)	(-1.25)	(-1.16)	(-1.15)	(-0.63)	(-0.63)	(1.29)	(1.30)	(-0.71)	(-0.70)	(1.17)	(1.18)	(1.55)	(1.56)	(-0.13)	(-0.13)
Internat.	1.304**	0.795**	1.308*	0.797**	1.312**	0.800**	1.175*	0.716*	1.860***	1.134***	1.235*	0.753*	1.848**	1.127***	1.780**	1.085***	1.287**	0.785**
	(1.96)	(1.97)	(1.95)	(1.97)	(1.96)	(1.97)	(1.74)	(1.75)	(3.06)	(3.13)	(1.81)	(1.82)	(3.11)	(3.18)	(3.19)	(3.26)	(2.12)	(2.14)
CEO don. to Trump			-0.084	-0.019														
			(-0.23)	(-0.23)														
CEO Repub.					-0.875	-0.049												
					(-1.01)	(-0.99)												
Connect							0.858**	0.073***	0.609	0.051								
							(2.32)	(2.75)	(1.43)	(1.55)								
No. of conn. to Trump											0.468*	0.047*						
											(1.71)	(1.93)						
Compet conn. to Trump									3.246***	0.189***			3.294***	0.192***	3.237**	0.188***		
									(6.82)	(10.17)			(6.77)	(10.29)	(6.65)	(9.68)		
Compet tweeted															2.174**	0.068***	2.430***	0.076***
															(4.02)	(5.19)	(3.90)	(6.56)
No. of obs.	446		446		446		446		446		446		446		446		446	
Pseudo R^2	0.243		0.244		0.246		0.256		0.328		0.305		0.423		0.334		0.286	
Fixed effect	No		No		No		No		No		No		No		No		No	

Table 2.3.1 Logistic regression fixed effects results from Trump's all statements of negative tone

The table reports coefficient estimates of logistic regression where the dependent variable is a dummy equal to one if a firm is explicitly mentioned by Trump statements in a negative linguistic tone, and zero otherwise, in the period from June 2015 to June 2017. Elasticity is calculated as d(ln F)/d(ln x), where d is the first derivative, ln (F) is the natural logarithm of the density function and ln (x) is the natural logarithm of the explanatory variable and is evaluated at the sample means of the explanatory variables. In addition to the control variables which include company size (log of total assets), leverage (total debt to total capital), profitability (return on assets), Altman z-score (likelihood of bankruptcy), marginal tax rate (the amount of tax paid on an additional dollar of income) and media excluding (control for non-media company effect), I control for company internationalization (change of foreign assets as a % of total assets in the tweeting period), CEO donation to Trump (whether firm's top management donates to Trump), CEO Republican (dummy variable equal to one if firm's top management is inclined towards the Republicans party, and zero otherwise), firm's connection to Trump, firm's competitor connection to Trump, competitor tweeted (equals one if firm's competitor is tweeted by Trump and zero otherwise) and firm's number of connection channels to Trump. One, two, and three asterisks indicate a significance level of 10%, 5%, and 1%, respectively.

	Dependent variable is all statements of negative tone																	
	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)		(9)	
	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.
Size	3.228***	12.287***	3.301***	12.571***	3.246***	12.364***	2.851***	10.823***	3.348***	12.656**	2.972***	11.292***	3.673***	13.924***	3.378***	12.690***	3.100***	1.718***
	(5.26)	(5.12)	(5.10)	(4.96)	(5.26)	(5.12)	(4.64)	(4.54)	(3.76)	(3.66)	(4.84)	(4.73)	(3.65)	(3.53)	(4.32)	(4.20)	(5.14)	(5.01)
Lever.	-0.084	-0.034	-0.076	-0.031	-0.069	-0.028	-0.111	-0.045	-0.465	-0.190	-0.107	-0.044	-0.471	-0.193	-0.628	-0.254	-0.116	-0.048
	(-0.23)	(-0.23)	(-0.20)	(-0.20)	(-0.19)	(-0.19)	(-0.29)	(-0.29)	(-0.48)	(-0.48)	(-0.29)	(-0.29)	(-0.48)	(-0.48)	(-0.62)	(-0.61)	(-0.27)	(-0.26)
Profit.	6.389**	0.500**	6.242**	0.489**	6.127*	0.480**	5.934*	0.462**	7.270*	0.558*	6.177**	0.481**	7.651*	0.589*	8.718**	0.662**	7.518**	0.581**
	(2.04)	(2.09)	(1.96)	(2.01)	(1.94)	(2.00)	(1.95)	(2.00)	(1.77)	(1.79)	(2.02)	(2.08)	(1.78)	(1.80)	(2.09)	(2.12)	(2.38)	(2.45)
Altman	0.060	0.176	0.063	0.184	0.057	0.167	0.064	0.188	0.042	0.123	0.059	0.173	0.041	0.121	0.019	0.056	0.036	0.105
z-score	(0.80)	(0.81)	(0.83)	(0.84)	(0.76)	(0.77)	(0.91)	(0.93)	(0.41)	(0.41)	(0.83)	(0.85)	(0.37)	(0.37)	(0.16)	(0.17)	(0.41)	(0.41)
Marg.	1.400*	0.055**	1.403*	0.055**	1.330*	0.052**	1.415*	0.055**	0.662	0.025	1.409*	0.055**	0.628	0.024	0.808	0.030	1.525*	0.059**
Tax rate	(1.75)	(2.13)	(1.76)	(2.15)	(1.66)	(2.00)	(1.76)	(2.16)	(0.62)	(0.66)	(1.76)	(2.16)	(0.60)	(0.65)	(0.72)	(0.78)	(1.89)	(2.36)
Media	-0.681	-0.591	-0.706	-0.613	-0.625	-0.542	-0.375	-0.324	1.028	0.886	-0.452	-0.391	0.874	0.756	1.354	1.161	-0.179	-0.154
excl.	(-0.82)	(-0.81)	(-0.84)	(-0.84)	(-0.74)	(-0.74)	(-0.44)	(-0.44)	(0.96)	(0.96)	(-0.53)	(-0.53)	(0.79)	(0.79)	(1.25)	(1.26)	(-0.21)	(-0.21)
Intern.	1.334**	0.853**	1.332**	0.852**	1.342**	0.859**	1.224*	0.779*	2.362**	1.494**	1.275*	0.813*	2.429**	1.541**	2.118**	1.330**	1.249**	0.792**
	(2.03)	(2.05)	(2.02)	(2.03)	(2.01)	(2.03)	(1.84)	(1.86)	(2.43)	(2.41)	(1.94)	(1.95)	(2.41)	(2.39)	(2.41)	(2.41)	(1.97)	(1.99)
CEO don. to Trump			-0.194	-0.048														
			(-0.43)	(-0.43)														
CEO Repub.					-1.397	-0.080												
					(-1.03)	(-1.01)												
Connect							1.033*	0.092**	0.608	0.055								
							(1.92)	(2.16)	(0.92)	(0.96)								
No. of conn. to Trump											0.556	0.059						
											(1.31)	(1.44)						
Compet conn. to Trump									4.095***	0.257***			4.237***	0.269***	3.909***	0.239***		
									(4.60)	(4.21)			(4.41)	(3.94)	(4.78)	(4.72)		
Compet tweeted															2.591**	0.082***	2.834***	0.091***
															(2.51)	(3.29)	(3.24)	(5.02)
No. of obs.	446		446		446		446		446		446		446		446		446	
Pseudo R^2	0.330		0.332		0.240		0.430		0.282		0.208		0.247		0.281		2.874	
Fixed effect	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	

Table 2.4 Logistic regression results from Trump's all statements of non-negative tone

The table reports coefficient estimates of logistic regression where the dependent variable is a dummy equal to one if a firm is explicitly mentioned by Trump statements in a non-negative linguistic tone, and zero otherwise, in the period from June 2015 to June 2017. Elasticity is calculated as d(ln F)/d(ln x), where d is the first derivative, ln (F) is the natural logarithm of the density function and ln (x) is the natural logarithm of the explanatory variable and is evaluated at the sample means of the explanatory variables. In addition to the control variables which include company size (log of total assets), leverage (total debt to total capital), profitability (return on assets), Altman z-score (likelihood of bankruptcy), marginal tax rate (the amount of tax paid on an additional dollar of income) and media excluding (control for non-media company effect), I control for company internationalization (change of foreign assets as a % of total assets in the tweeting period), CEO donation to Trump (whether firm's top management donates to Trump), CEO Republican (dummy variable equal to one if firm's top management is inclined towards the Republicans party, and zero otherwise), firm's connection to Trump, firm's competitor connection to Trump, competitor tweeted (equals one if firm's competitor is tweeted by Trump and zero otherwise) and firm's number of connection channels to Trump. One, two, and three asterisks indicate a significance level of 10%, 5%, and 1%, respectively.

	Dependent variable is all statements of non-negative tone																	
	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)		(9)	
	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.
Size	1.427***	4.521***	1.363***	4.321***	1.427***	4.524***	1.157***	3.667***	1.164***	3.688***	1.176***	3.728***	1.375***	4.358***	1.360***	4.311***	1.417***	4.491***
	(4.30)	(4.21)	(3.95)	(3.86)	(4.30)	(4.21)	(3.45)	(3.37)	(3.02)	(2.96)	(3.41)	(3.33)	(3.49)	(3.42)	(3.43)	(3.36)	(4.13)	(4.02)
Lever.	0.409*	0.115*	0.397*	0.112*	0.405*	0.114*	0.376	0.106	0.262	0.073	0.358	0.101	0.308	0.087*	0.285	0.080	0.378*	0.106*
	(1.76)	(1.82)	(1.65)	(1.70)	(1.71)	(1.76)	(1.46)	(1.49)	(1.40)	(1.44)	(1.26)	(1.29)	(1.61)	(1.66)	(1.53)	(1.57)	(1.78)	(1.83)
Profit.	4.104**	0.245**	4.181**	0.250**	4.122**	0.246**	3.690*	0.220*	3.668	0.219*	3.766*	0.225**	4.007*	0.239*	4.541*	0.271**	4.716**	0.282**
	(2.04)	(2.11)	(2.14)	(2.22)	(2.05)	(2.12)	(1.87)	(1.93)	(1.60)	(1.66)	(1.91)	(1.97)	(1.69)	(1.75)	(1.94)	(2.02)	(2.37)	(2.46)
Altman	0.036	0.086	0.034	0.081	0.036	0.086	0.040	0.097	0.012	0.028	0.035	0.086	0.006	0.015	-0.009	-0.023	0.015	0.037
z-score	(0.78)	(0.79)	(0.75)	(0.76)	(0.78)	(0.80)	(0.91)	(0.93)	(0.26)	(0.26)	(0.80)	(0.82)	(0.13)	(0.13)	(-0.19)	(-0.19)	(0.34)	(0.35)
Marg.	1.412***	0.040***	1.434**	0.040***	1.417**	0.040***	1.389**	0.039***	1.257	0.035*	1.394***	0.039***	1.261	0.035*	1.353*	0.038**	1.515***	0.043***
Tax rate	(2.60)	(3.33)	(2.48)	(3.14)	(2.53)	(3.22)	(2.57)	(3.31)	(1.52)	(1.74)	(2.58)	(3.32)	(1.56)	(1.78)	(1.73)	(2.00)	(2.81)	(3.62)
Media	-0.192	-0.138	-0.175	-0.126	-0.197	-0.141	0.055	0.039	1.183**	0.853**	0.095	0.068	1.007*	0.727*	1.278**	0.923**	0.101	0.073
excl.	(-0.53)	(-0.53)	(-0.49)	(-0.48)	(-0.55)	(-0.54)	(0.14)	(0.14)	(2.00)	(2.02)	(0.23)	(0.23)	(1.84)	(1.86)	(2.19)	(2.21)	(0.29)	(0.29)
Intern.	0.681	0.354	0.672	0.349	0.681	0.354	0.581	0.302	0.745	0.387	0.597	0.310	0.820	0.426	0.818	0.425	0.708	0.368
	(1.38)	(1.39)	(1.37)	(1.38)	(1.38)	(1.39)	(1.18)	(1.19)	(1.40)	(1.42)	(1.21)	(1.22)	(1.58)	(1.60)	(1.59)	(1.62)	(1.43)	(1.45)
CEO don. to Trump			0.251	0.048														
			(0.91)	(0.96)														
CEO Repub.					0.067	0.003												
					(0.14)	(0.15)												
Conn.							0.920***	0.059***	0.706**	0.045***								
							(3.00)	(4.23)	(2.29)	(2.73)								
No. of conn. to Trump											0.755***	0.054***						
											(2.62)	(3.72)						
Compet conn. to Trump									2.947***	0.079***			3.002***	0.080***	2.957***	0.079***		
									(7.11)	(6.46)			(7.10)	(6.24)	(7.16)	(6.60)		
Compet tweeted															1.505***	0.040***	1.734***	0.046***
															(2.61)	(3.75)	(2.71)	(5.16)
No. of obs.	446		446		446		446		446		446		446		446		446	
Pseudo R^2	0.112		0.113		0.112		0.126		0.267		0.145		0.260		0.278		0.133	
Fixed effect	No		No		No		No		No		No		No		No		No	

Table 2.4.1 Logistic regression fixed effects results from Trump's all statements of non-negative tone

The table reports coefficient estimates of logistic regression where the dependent variable is a dummy equal to one if a firm is explicitly mentioned by Trump statements in a non-negative linguistic tone, and zero otherwise, in the period from June 2015 to June 2017. Elasticity is calculated as d(ln F)/d(ln x), where d is the first derivative, ln (F) is the natural logarithm of the density function and ln (x) is the natural logarithm of the explanatory variable and is evaluated at the sample means of the explanatory variables. In addition to the control variables which include company size (log of total assets), leverage (total debt to total capital), profitability (return on assets), Altman z-score (likelihood of bankruptcy), marginal tax rate (the amount of tax paid on an additional dollar of income) and media excluding (control for non-media company effect), I control for company internationalization (change of foreign assets as a % of total assets in the tweeting period), CEO donation to Trump (whether firm's top management donates to Trump), CEO Republican (dummy variable equal to one if firm's top management is inclined towards the Republicans party, and zero otherwise), firm's connection to Trump, firm's competitor connection to Trump, competitor tweeted (equals one if firm's competitor is tweeted by Trump and zero otherwise) and firm's number of connection channels to Trump. One, two, and three asterisks indicate a significance level of 10%, 5%, and 1%, respectively.

	Dependent variable is all statements of non-negative tone																	
	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)		(9)	
	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.
Size	1.782***	6.096***	1.735***	5.936***	1.784***	6.102***	1.503***	5.122***	1.402***	4.725***	1.519***	5.186***	1.409***	4.751***	1.578***	5.329***	1.733***	5.912***
	(4.73)	(4.72)	(4.50)	(4.50)	(4.73)	(4.71)	(3.82)	(3.81)	(3.31)	(3.31)	(3.87)	(3.88)	(3.36)	(3.37)	(3.81)	(3.82)	(4.50)	(4.51)
Lever.	0.307	0.096	0.299	0.094	0.306	0.096	0.300	0.093	0.146	0.045	0.303	0.094	0.126	0.038	0.170	0.052	0.304	0.095
	(1.30)	(1.39)	(1.25)	(1.34)	(1.29)	(1.39)	(1.26)	(1.33)	(0.65)	(0.68)	(1.23)	(1.28)	(0.57)	(0.59)	(0.72)	(0.75)	(1.30)	(1.38)
Profit.	4.434**	0.304**	4.481**	0.307**	4.443**	0.305**	4.061**	0.277**	4.651**	0.307**	4.112**	0.280**	4.681**	0.308**	5.528**	0.367**	4.957**	0.340**
	(2.23)	(2.31)	(2.26)	(2.34)	(2.23)	(2.31)	(2.06)	(2.13)	(2.18)	(2.23)	(2.08)	(2.15)	(2.19)	(2.25)	(2.46)	(2.53)	(2.40)	(2.50)
Altman	0.021	0.058	0.023	0.063	0.021	0.058	0.014	0.039	0.051	0.136	0.017	0.049	0.052	0.140	0.088	0.234	0.048	0.131
z-score	(0.39)	(0.39)	(0.42)	(0.41)	(0.39)	(0.38)	(0.27)	(0.27)	(0.84)	(0.82)	(0.33)	(0.33)	(0.87)	(0.86)	(1.20)	(1.17)	(0.76)	(0.74)
Marg.	1.329	0.043*	1.344	0.043*	1.335	0.043*	1.292	0.042*	1.163	0.036	1.300	0.042*	1.162	0.036	1.164	0.036	1.365	0.044*
Tax rate	(1.36)	(1.72)	(1.36)	(1.70)	(1.36)	(1.72)	(1.37)	(1.74)	(1.02)	(1.10)	(1.36)	(1.73)	(1.01)	(1.10)	(1.01)	(1.10)	(1.38)	(1.77)
Media	-0.340	-0.265	-0.330	-0.257	-0.344	-0.268	-0.056	-0.043	1.184	0.911	-0.016	-0.012	1.236	0.951	1.367	1.053	0.112	0.087
excl.	(-0.49)	(-0.48)	(-0.47)	(-0.47)	(-0.49)	(-0.49)	(-0.08)	(-0.08)	(1.38)	(1.39)	(-0.02)	(-0.02)	(1.43)	(1.44)	(1.48)	(1.49)	(0.15)	(0.15)
Intern.	0.481	0.277	0.491	0.283	0.483	0.278	0.355	0.204	0.528	0.298	0.373	0.215	0.540	0.305	0.667	0.377	0.491	0.282
	(1.09)	(1.10)	(1.11)	(1.12)	(1.09)	(1.10)	(0.78)	(0.79)	(1.04)	(1.05)	(0.82)	(0.83)	(1.06)	(1.07)	(1.31)	(1.33)	(1.09)	(1.11)
CEO don. to Trump			0.190	0.040														
			(0.56)	(0.58)														
CEO Repub.					0.064	0.003												
					(0.10)	(0.10)												
Conn.							1.152**	0.078***	0.905*	0.062**								
							(2.48)	(3.41)	(1.77)	(2.12)								
No. of conn. to Trump											0.989**	0.073***						
											(2.55)	(3.62)						
Compet conn. to Trump									3.582***	0.097***			3.602***	0.097***	3.596***	0.099***		
									(6.15)	(4.81)			(6.15)	(4.84)	(6.06)	(4.61)		
Compet tweeted															2.481***	0.061***	2.692***	0.063***
															(2.60)	(5.00)	(3.21)	(7.28)
No. of obs.	446		446		446		446		446		446		446		446		446	
Pseudo R^2	0.200		0.250		0.251		0.310		0.197		0.309		0.218		0.217		0.313	
Fixed effect	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	

2.7 Event study

2.7.1 Descriptive Statistics

Table 2.5 reports statistical summary of all 134 statements and 111 companies mentioned by Trump in the period from June 2015 to June 2017. The sample totals to 274 observations. 24.8% are Twitter statements and 75.1% are media statements. In 27.7% Trump statements do not mention media companies (see, Panel 2 of Table 2.5). Panel 3 of Table 2.5 categorizes the statements according to their linguistic tone using the methodology described in Section 2.4.2. In 71.5% Trump statements carry negative tone. Panel 4 describes the top management political orientation of the companies. In 12% of the observations the CEO of the company has donated to the Republican party and 24% to the Democratic party. Panel 5 provides descriptive statistics on companies' business connections to Trump. For instance, in 48.9% of the observations a company of my sample is connected to Trump. Panel 6 of Table 2.5 reports basic financial information for the sample of companies and a summary statistic of the primary measure of company performance, "cumulative average abnormal returns (CARs)" – the calculation of which is discussed in Section 2.5, the "abnormal trading volume (AV)" and stock price "volatility", which are also covered in Section 2.5.

Table 2.5 Descriptive statistics (Event Study & Cross-sectional analysis)

The table reports descriptive statistics of Trump's 134 statements and 111 companies taken into consideration from June 2015 to June 2017. Panel 1 presents the total number of observations. Panel 2 categorizes the statements by type of source. Panel 3 categorizes the statements by their linguistic tone. Panel 4 categorizes the companies by political orientation. Panel 5 summarizes the companies connected to Trump and the number of connection channels he has with specific companies. Panel 6 presents additional firm level financial variables.

	Mean	Min	p1	p25	p50	p75	p99	Max	St. dev.	Obs.
Panel 1. All Statements										274
Panel 2 Statements type										
Twitter statements	0.248	0	0	0	0	0	1	1	0.432	274
Media statements	0.751	0	0	1	1	1	1	1	0.433	274
Media excluding	0.277	0	0	0	1	1	1	1	0.448	274
Panel 3. Statements categorized by linguistic tone										
Negative	0.715	0	0	0	1	1	1	1	0.448	274
Non-Negative	0.284	0	0	0	0	0	1	1	0.346	274
Panel 4. Companies' political orientation										
CEO Republican	0.120	0	0	0	0	0	1	1	0.326	274
CEO Democrat	0.240	0	0	0	0	0	1	1	0.428	274
Panel 5. Company connection to Trump and family										
Connect	0.489	0	0	0	0	1	1	1	0.501	274
Connection channels no.	0.861	0	0	0	0	1	10	10	1.451	274
Panel 6. Other financial variables										
Size	17.090	11.822	11.965	15.410	17.692	18.427	20.566	21.635	1.961	274
Profitability	5.151	-42.25	-35.44	3.63	5.97	9.56	23.800	40.14	9.576	274
Leverage	0.491	0	0	0.266	0.454	0.635	1.166	3.528	0.366	274
Altman z-score	1.623	-9.919	-0.075	0	0.172	2.421	12.50	56.92	3.303	274
CEO donation to Trump	0.060	0	0	0	0	0	1	1	0.239	274
CAR [0,5]	-0.003	-0.157	-0.140	-0.022	-0.003	0.016	0.123	0.187	0.042	274
CAR [0,0]	0.001	-0.088	-0.014	-0.007	-0.002	0.006	0.044	0.044	0.015	274
CAR [0,1]	0.001	-0.145	-0.101	-0.016	-0.014	0.015	0.100	0.128	0.030	274
Abnormal trading volume	-0.082	-0.973	-0.973	-0.813	-0.561	0.136	3.121	3.121	1.115	274
Volatility	1.466	0.194	0.265	0.789	1.149	1.849	6.099	8.511	1.106	274

2.7.2 Event Study Results

In this subsection I present the results of the event-study methodology. Table 2.6 depicts the CARs around the statements from the one-factor market model. Panel 1 of Table 2.6 shows the CARs results for all statements - i.e. events, in my sample. In Panel 1, the CARs on the event days are negative for all three event windows [0, 5], [0, 0], and [0, 1] (-0.393%, -0.114% and -0.400% respectively) and statistically significant. For example, the [0, 1] event window is statistically significant at 1% significance level with Patell Z-score of -2.731.

In Panel 2 of Table 2.6, Trump's statements are categorized according to their linguistic tone. Consistent with Figure 2.1b and Figure 2.1c - which for visual presentation implements a longer event window, the statements followed by a non-negative linguistic tone result in non-negative but statistically insignificant CARs at all three event windows. The statements of negative linguistic tone result in negative statistically significant CARs for the [0, 0] and [0, 1] event windows (-0.184% and -0.513% respectively). From this panel, one can draw a conclusion that statements carrying certain linguistic tone can significantly impact companies' CARs within a shorter time-span (as in my case [0, 0] or [0, +1]). The pronounced effect in the shorter-time span is typical for Twitter statements because of their fast update and circulation in the social media.

Panel 3 of Table 2.6 presents CARs results for the before-Election Day and after-Election Day period statements in my sample. The Election Day occurred on 08.11.2016, thus the CARs results are based on 56 observations in the before-Election Day period and 218 observations in the after-Election Day period. The before-Election Day CARs for the [0, 5] event window is negative and statistically significant at 10% level (-0.340% with Patell Z-score of -1.647); however, I do not observe significant results for the other windows. The after-Election Day CARs are statistically significant for all three event windows and indicating a stronger effect. Four potential explanations exist for this reaction. First, Twitter was the primary communication channel with the market before the Election Day. Other channels such as presidential executive orders, numerous press releases and briefings contribute with additional information dissemination only after the Election Day (I record 56 observations before the Election Day and 2018 after the Election Day). Second, some of the after-election statements, especially tweets, were posted on the @POTUS account which although I do not use it in my analysis, it interacts in content with the @realDonaldTrump account and might affect the stock market response. Third, it seems investors took Trump statements more seriously after he gained political and socio-economic decision-making power (Ayers et al., 2005). Forth, the election of Donald Trump as the 45th President of the U.S. was not an expected outcome and it surprised most observers, see Massoud and Zhou (2018).

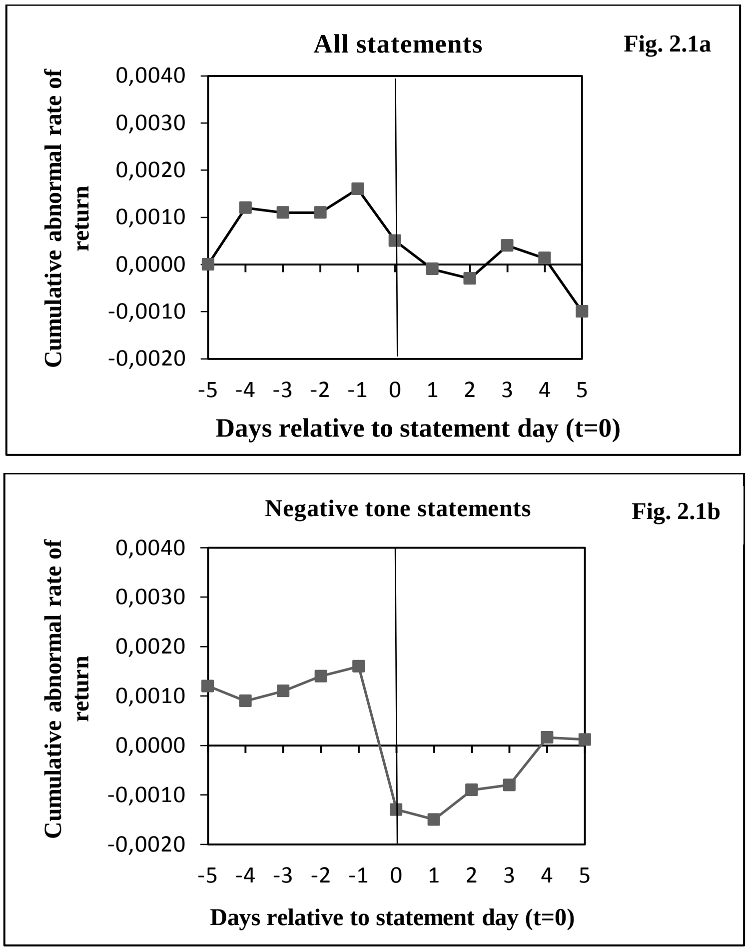
Panel 4 of Table 2.6 presents CARs results for the combination of after-Election Day statements and their linguistic tone. The non-negative linguistic tone contributes with 0.339%

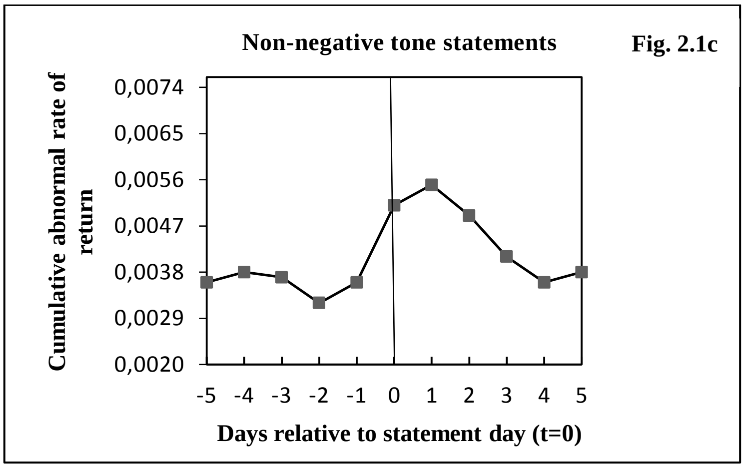
of CARs, whereas the after - Election Day statements of negative tone are mostly expressed in the [0, 5] event window with -0.722% and Patell Z-score of -2.586.

Panel 5 of Table 2.6 shows the CARs results for the statements which exclude observing media companies. The CARs are generally negative and significant (-0.543% with Patell Z-score of -3.019) at 1% significance level for the [0, 1] window.

Overall, the event study analysis points to an existing impact of the presidential candidate's public statements on the U.S. companies' stock returns. I stress that the event study results are weaker than the regression results reported in the next section due to the fact that I employ the non-overlapping selection criteria of the events which lowers the total number of observations available.

Figure 2.1 Cumulative Abnormal Returns





Notes: Fig. 2.1a – Fig. 2.1c depict the cumulative abnormal returns (CARs) around the event day (t=0) for stocks with exposure to Trump's media statements in the period from June 2015 to June 2017. The abnormal return on day t is calculated as the difference between the observed rate of return and the ex-post expected rate of return on day t. The one-factor market model $\boldsymbol{r_{i,t} = \alpha_0 + \beta_1 r_{m,t} + \varepsilon_t}$, where $\boldsymbol{r_{i,t}}$ is the return on stock $\boldsymbol{i}$ in period t and $\boldsymbol{r_{m,t}}$ is the S&P 500 return, is estimated using a 250-day estimation window. Fig. 2.1a depicts the CARs for all statements together. Fig. 2.1b and Fig. 2.1c categorize the statements by linguistic tone. The announcement selection procedure follows the *last/first* occurrence criteria which guarantees non-overlapping event windows during the period of observation.

Table 2.6 Event Study - cumulative average abnormal return results

The table depicts the cumulative average abnormal returns (CARs) around the statement day (t=0) for stocks with exposure to Trump's media statements in the period from June 2015 to June 2017. The abnormal return on day t is calculated as the difference between the observed rate of return and the ex-post expected rate of return on day t. The one-factor market model $\boldsymbol{r_{i,t} = \alpha_0 + \beta_1 r_{m,t} + \varepsilon_t}$, where $\boldsymbol{r_{i,t}}$ is the return on stock $\boldsymbol{i}$ in period t and $\boldsymbol{r_{m,t}}$ is the S&P 500 return, is estimated using a 250-day estimation window over three event windows: [0, +5], [0, 0] and [0, +1]. The second column reports the number of observations, the third column is each CAR value (in %) and fourth column reports the Patell Z-score where one, two, and three asterisks indicate a significance level of 10%, 5%, and 1%, respectively. Panel 1 to Panel 5 categorize the events by tone, time and industry type. The event selection procedure follows the *last/first* occurrence criteria which guarantees non-overlapping event windows during the period of observation.

Event Window	No. of observations	CAR (%)	Patell Z score
Panel 1. All Statements			
[0, +5]	274	-0.393	-1.967**
[0, 0]	274	-0.114	-1.646*
[0, +1]	274	-0.400	-2.731***
Panel 2. Statements categorized by linguistic tone			
Non-Negative			
[0, +5]	78	0.013	0.011
[0, 0]	78	0.194	0.085
[0, +1]	78	0.298	0.978
Negative			
[0, +5]	196	-0.081	-1.247
[0, 0]	196	-0.184	-2.047**
[0, +1]	196	-0.513	-3.240***
Panel 3. Before vs. After Election Day statements			
Before Election Day events			
[0, +5]	56	-0.340	-1.647*
[0, 0]	56	-0.009	-0.229
[0, +1]	56	-0.003	-0.750
After Election Day events			
[0, +5]	218	-0.357	-1.981**
[0, 0]	218	-0.002	-1.647*
[0, +1]	218	-0.456	-2.756***
Panel 4. After Election Day statements + linguistic tone			
Non-negative			
[0, +5]	76	0.034	0.136
[0, 0]	76	0.036	0.212
[0, +1]	76	0.339	1.648*

Negative			
[0, +5]	141	-0.722	-2.586***
[0, 0]	141	-0.261	-2.235**
[0, +1]	141	-0.612	-3.353***
Panel 5. Media excluding statements			
[0, +5]	76	0.180	1.421
[0, 0]	76	-0.150	-1.688*
[0, +1]	76	-0.543	-3.019***

2.7.3 Stock market reaction to Trump's public statements and their linguistic tone

Motivated by Chen et al. (2016) I test whether the linguistic tone used in Trump's public statements predicts stock market returns, affects the trading volume and the stock price volatility. Table 2.7 summarizes the results of the regression analysis in (3). Models 1 to 5 present regression results without industry fixed effects whereas models 6 to 10 include industry fixed effects (FF 30-Industry classification). Standard errors are clustered by firm (using their CUSIP - Committee on Uniform Securities Identification Procedures code).

The results from Table 2.7 (models 1 to 5) show that the effect of the negative linguistic tone of the statements is present and significant at 10% significance level when exercised upon the CAR [0, 5] and CAR [0, 1] event windows. For example, the statements carrying negative linguistic tone indicate a negative 1.022% to the CARs over six days period. Given that the average market capitalization of the firms in my sample is just about $8 billion, this translates to roughly $82 million in wealth reduction when Trump's statements are negative. Furthermore, the effect on the abnormal trading volume is negative i.e. the trading volume decreases after a statement with negative linguistic tone hits the public. The volatility of the stock prices increases, however for both the abnormal trading volume and volatility I do not find statistical support. The estimates for the control variables i.e. for firms' size, leverage, likelihood of bankruptcy, non-media company effect as well as the after-Election Day statements[23] show rather weak economic impact apart from companies' size and degree of leverage when observed over the [0, 1] event window.

In addition, models 6 to 10 of Table 2.7 present the estimates with industry fixed effects. This is to ensure that my results are not driven by any specific sector(s). Coefficients of the linguistic tone as well as for the control variables remain somewhat similar to the no-fixed effects models, although their economic significance is slightly lower.

To sum up, Table 2.7 shows evidence that the usage of negative linguistic tone by Trump predicts negative cumulative average abnormal returns, has impact on the trading volume and

[23] I control for after-Election Day statements impact motivated by Lau and Pomper (2002) who find that the period around the Election Day is characterized by intensified negative linguistic tone, most likely because the candidates prefer to criticize their opponent's positions. The effect magnitude is even larger after the Election Day since first, the investors adjust their expectations in the pre-Election Day period and become more risk aware to invest under the current political and socio-economic situation, and second, they perceive the events after the presidential elections to be more relevant since the President gains more decision-making power.

stock price volatility of the companies he explicitly tackles in his public statements. This result supports my hypothesis and contributes to past research suggesting that presidential candidates often attempt to target certain entities by using negative tone when criticizing in the public (Wagner et al., 2017). Furthermore, the insights from Table 2.7 touch upon the question of whether it is optimal for The President to communicate his rhetoric primarily through social media tools where unexpected announcements and unclear statements can instantly bring or wipe out significant amount of shareholder value in terms of dollars. These findings comply with Pastor and Veronesi (2013)'s theoretical model that explains how political news, such as president or prime minister announcements, can revise investor expectations regarding government intentions to modify certain policies in the future. The evidence shows that the stock market is sensitive to news coming from politicians who although may not be in power yet, they influence company stock returns.

2.7.4 Stock market reaction to companies' business and political connections to Trump

Acemoglu et al. (2016) find that any connection of a high-government official to a company top management can matter greatly. Hong and Kostovetsky (2012) conclude that it is possible for investors with political preferences to pay more attention to political rhetoric when the presidential candidate of their favored political party gives a speech. Inspired by previous research, I hypothesize that companies' business and political connections to Trump are likely to influence companies' stocks, trading volume, and stock price volatility. Table 2.8 summarizes the results. Following the previous pattern, models 1 to 5 present regression results without industry fixed effects whereas models 6 to 10 include industry fixed effects. The standard errors are clustered by firm.

The coefficient in front of the "number of connection channels" in which certain company is related to Trump, suggests rather positive impact on the CARs where each additional channel brings about 0.278% (see, event window [0, 5]) of return benefit. More intuitively, this translates to roughly $21 million on average in wealth creation for firm's shareholders for every additional business connection between the firm and Trump. The effect of the "number of connection channels" appears to be significant for the abnormal volume too, where with each additional channel the abnormal volume drops of about 0.161%. Furthermore, the results show positive and statistically significant at 5% level impact on the CARs, and negative impact on the abnormal volume and volatility when companies' top management is donation-inclined towards the Republican party. This result is consistent with Massoud and Zhou (2018) who find that firm's connection to the President established via donations to his political party brings benefits to that firm's future returns.

Table 2.7 Cross-sectional regression: stock market reaction to Trump's public statements and their linguistic tone
The table reports coefficient estimates of OLS regressions of cumulative average abnormal returns (CARs), abnormal trading volume (AV) and volatility around Trump's statements in the period from June 2015 to June 2017. Each announcement date is considered as an event day (t=0). Abnormal returns are calculated using the one-factor market model $r_{i,t} = \alpha_0 + \beta_1 r_{m,t} + \varepsilon_t$, where $r_{i,t}$ is the return on stock i in period t and $r_{m,t}$ is the S&P 500 return, is estimated using a 250-day estimation window over [0,5], [0,0] and [0,1] event windows. Abnormal trading volume is calculated as the difference between the trading volume $V_{i,t}$ and mean trading volume of the previous seven days divided by the mean trading volume of the previous seven days. Volatility is calculated as $\hat{\sigma}_{it}{}^2 = (H_{it} - C_{it})(H_{it} - O_{it}) + (L_{it} - C_{it})(L_{it} - O_{it})$ where O_{it}, C_{it}, H_{it} and L_{it} are the natural log of the opening, closing, high and low prices for company i on day t, respectively. Statements' linguistic tone denotes the connotation of the message transmitted by Trump. Control variables include company size (log of total assets), leverage (total debt to total capital), profitability (return on assets), Altman z-score (likelihood of bankruptcy), and media excl. (control for non-media company effect). Columns (6) – (10) consider industry fixed effects. One, two, and three asterisks indicate a significance level of 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Dependent variable is CAR [0,5]	Dependent variable is CAR [0,0]	Dependent variable is CAR [0,1]	Dependent variable is AV	Dependent variable is volatility	Dependent variable is CAR [0,5]	Dependent variable is CAR [0,0]	Dependent variable is CAR [0,1]	Dependent variable is AV	Dependent variable is volatility
Size	0.043	0.065	0.211**	0.279***	0.052	0.210	0.097	0.289**	0.240*	0.389
	(0.31)	(0.77)	(2.09)	(4.28)	(0.35)	(0.87)	(0.99)	(2.00)	(1.73)	(1.02)
Leverage	1.049*	0.578	1.019**	0.375	-0.836	1.025	0.453	1.178	1.525	-1.871**
	(1.86)	(1.51)	(2.52)	(0.91)	(-1.22)	(0.62)	(0.77)	(0.97)	(1.57)	(-2.11)
Profitability	-0.015	-0.032**	-0.029	-0.012	0.018	-0.082	-0.022	-0.035	-0.002	0.045
	(-0.50)	(-2.05)	(-1.54)	(-1.02)	(1.30)	(-1.37)	(-1.29)	(-1.45)	(-0.06)	(0.95)
Altman z-score	-0.100***	-0.004	-0.027*	0.037**	0.062	-0.002	-0.068*	-0.018	0.086**	-0.107
	(-3.63)	(-0.23)	(-1.64)	(2.11)	(0.75)	(-0.03)	(-1.65)	(-0.33)	(2.54)	(-1.27)
Media excl.	-1.043**	-0.524*	-0.517	0.342**	-0.096	0.897	-1.982**	-0.362	0.185	2.528
	(-2.03)	(-1.79)	(-1.58)	(1.97)	(-0.11)	(0.85)	(-2.17)	(-0.34)	(0.30)	(1.05)
Negative	-1.022*	-0.205	-0.638*	-0.222	0.429	-1.021*	-0.161	-0.631	0.050	0.120
	(-1.92)	(-1.11)	(-1.76)	(-1.00)	(1.59)	(-1.90)	(-1.51)	(-1.19)	(0.34)	(0.48)
After E.D. statements	0.414	0.322	0.167	0.319*	-0.005	0.764	0.047	0.083	0.242	0.404
	(0.53)	(1.38)	(0.60)	(1.86)	(-0.03)	(0.82)	(0.64)	(0.14)	(1.31)	(0.83)
Number of obs.	274	274	274	274	274	274	274	274	274	274
R-squared	0.180	0.124	0.105	0.317	0.066	0.341	0.441	0.346	0.649	0.616
Fixed Effects	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes

Observing the effect of the political factors and companies' connection to Trump on the abnormal volume and stock price volatility, one can conclude that the negative coefficients appearing are rather expected since President's announcements reduce the uncertainty prevailing in the market. The analysis in Table 2.8 incorporates the following set of control variables. Firm size is included as a control because if Trump has more interaction with larger firms, then the observed performance of Trump-connected companies could be due to their size rather than to their connections. Altman Z-score, profitability and leverage are also important controls because they indicate how vulnerable and hard each company is influenced in the period of high pre- and post- election period uncertainty. Finally, media excluding control is added to control for the potential impact of the companies which do not operate in the media sector.

To sum up, Table 2.8 provides evidence supporting the hypothesis that companies' business and political connections to Trump are likely to influence companies' stocks, trading volume and stock price volatility. Moreover, access to government officials can be hugely beneficial especially when the connection between the government official and the third party are personal Acemoglu et al. (2016).

2.8 Robustness

2.8.1 Logistic regression robustness test results

In this subsection, I present robustness test results for the logit models. Table 2.9 and Table 2.9.1 present the results from the logit analysis together with the elasticity (economic importance) for Trump's Twitter statements being a dummy variable equal to one if a firm is explicitly tweeted by Trump and zero otherwise. The results are obtained on a sample of 67 company-specific Twitter statements. In addition, Table 2.9.1 present the estimates with industry fixed effects.

The results comply with my previous findings and suggest that the likelihood of a firm been tweeted by Trump depends on the size of the firm. For the profitability, marginal tax rate and for firm's presence on the international markets, unlike before, I observe statistically insignificant estimates. Furthermore, Trump appears to tweet about the firms to which he is connected to and for those firms' competitors. An important point to be noted is that I also find positive and statistically significant estimates for company's top management donation variables. For example, in model 2 of Table 2.9 being financial donor to Trump translates to 0.286% higher probability to be mentioned by him in his tweets. To sum up, these results provide further evidence of the robustness of my main result from the logit analysis.

Table 2.8 Cross-sectional regression: stock market reaction to companies' business and political connections to Trump

The table reports coefficient estimates of OLS regressions of cumulative average abnormal returns (CARs), abnormal trading volume (AV) and volatility around Trump's statements in the period from June 2015 to June 2017. Each announcement date is considered as an event day (t=0). Abnormal returns are calculated using the one-factor market model $\boldsymbol{r_{i,t}} = \boldsymbol{\alpha_0} + \boldsymbol{\beta_1 r_{m,t}} + \boldsymbol{\varepsilon_t}$, where $\boldsymbol{r_{i,t}}$ is the return on stock $\boldsymbol{i}$ in period t and $\boldsymbol{r_{m,t}}$ is the S&P 500 return, is estimated using a 250-day estimation window over [0,5], [0,0] and [0,1] event windows. Abnormal trading volume (AV) is calculated as the difference between the trading volume $\boldsymbol{V_{i,t}}$ and mean trading volume of the previous seven days divided by the mean trading volume of the previous seven days. Volatility is calculated as $\boldsymbol{\hat{\sigma}_{it}}^2 = (\boldsymbol{H_{it}} - \boldsymbol{C_{it}})(\boldsymbol{H_{it}} - \boldsymbol{O_{it}}) + (\boldsymbol{L_{it}} - \boldsymbol{C_{it}})(\boldsymbol{L_{it}} - \boldsymbol{O_{it}})$ where $\boldsymbol{O_{it}}, \boldsymbol{C_{it}}, \boldsymbol{H_{it}}$ **and** $\boldsymbol{L_{it}}$ are the natural log of the opening, closing, high and low prices for company $\boldsymbol{i}$ on day $\boldsymbol{t}$, respectively. Control variables include company size (log of total assets), leverage (total debt to total capital), profitability (return on assets), Altman z-score (likelihood of bankruptcy), and media excl. (control for non-media company effect). Columns (6) – (10) consider industry fixed effects. One, two, and three asterisks indicate a significance level of 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Dependent variable is CAR [0,5]	Dependent variable is CAR [0,0]	Dependent variable is CAR [0,1]	Dependent variable is AV	Dependent variable is volatility	Dependent variable is CAR [0,5]	Dependent variable is CAR [0,0]	Dependent variable is CAR [0,1]	Dependent variable is AV	Dependent variable is volatility
Size	-0.074 (-0.46)	-0.002 (-0.03)	0.148 (1.27)	0.335*** (4.53)	-0.193*** (-4.27)	-0.094 (-0.28)	-0.011 (-0.06)	0.406* (1.95)	0.022 (0.15)	-0.298** (-2.59)
Leverage	0.774 (1.53)	0.567 (1.56)	0.979** (2.49)	0.443 (1.10)	0.172 (0.79)	0.560 (0.36)	0.583 (1.00)	1.375 (0.99)	1.533* (1.92)	0.218 (0.85)
Profitability	-0.002 (-0.05)	-0.027* (-1.84)	-0.023 (-1.18)	-0.019 (-1.65)	-0.022** (-2.42)	-0.078 (-1.30)	-0.018 (-0.90)	-0.045 (-1.63)	-0.009 (-0.40)	-0.009 (-0.39)
Altman z-score	-0.095*** (-3.21)	-0.008 (-0.52)	-0.023 (-1.39)	0.047*** (4.19)	0.019** (2.12)	-0.018 (-0.22)	-0.059* (-1.88)	-0.006 (-0.11)	0.094*** (2.92)	0.007 (0.26)
Media excl.	-0.751 (-1.63)	-0.720*** (-2.67)	-0.581* (-1.93)	0.450*** (2.62)	0.447*** (3.40)	-0.707 (-0.64)	-2.048*** (-2.90)	0.244 (0.21)	0.481 (0.77)	0.303 (0.66)
No. connection channels	0.278** (1.99)	0.104 (1.15)	0.102 (1.05)	-0.161** (-2.31)	-0.024 (-0.56)	1.034 (0.85)	0.213 (1.61)	0.142 (0.70)	-0.703*** (-3.36)	-0.288 (-0.92)
CEO Republican	2.170** (2.23)	0.535 (1.18)	0.793 (1.62)	-0.632** (-2.60)	0.042 (0.19)	1.276 (1.30)	0.033 (0.07)	0.315 (0.34)	-0.635*** (-2.68)	0.048 (0.07)
CEO Democrat	-0.679 (-1.49)	-0.056 (-0.16)	-0.324 (-1.02)	0.242 (0.96)	0.069 (0.46)	-0.828 (-1.58)	-0.373 (-1.16)	-0.237 (-0.57)	0.494 (1.51)	0.074 (0.33)
Negative	-1.218** (-2.39)	-0.166 (-0.89)	-0.677 (-1.97)	-0.018 (-0.12)	0.066 (0.30)	-1.188** (-2.11)	-0.093 (-0.89)	-0.629 (-1.16)	-0.209 (-1.00)	0.163 (0.44)
CEO donation to Trump	1.064** (1.97)	0.267 (0.88)	0.334 (0.87)	-0.301 (-1.00)	0.051 (0.26)	0.935 (0.91)	0.809* (1.75)	0.277 (0.46)	-0.540 (-1.01)	0.026 (0.09)
Number of obs.	274	274	274	274	274	274	274	274	274	274
R-squared	0.121	0.158	0.119	0.384	0.230	0.341	0.374	0.347	0.703	0.436
Fixed effect	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes

Table 2.9 Logistic regression robustness test results

The table reports coefficient estimates of logistic regression where the dependent variable is a dummy equal to one if a firm is explicitly tweeted by Trump and zero otherwise in the period from June 2015 to June 2017. Elasticity is calculated as d(ln F)/d(ln x), where d is the first derivative, ln (F) is the natural logarithm of the density function and ln (x) is the natural logarithm of the explanatory variable and is evaluated at the sample means of the explanatory variables. In addition to the control variables which include company size (log of total assets), leverage (total debt to total capital), profitability (return on assets), Altman z-score (likelihood of bankruptcy), marginal tax rate (the amount of tax paid on an additional dollar of income) and media excluding (control for non-media company effect), I control for company internationalization (change of foreign assets as a % of total assets in the tweeting period), CEO donation to Trump (whether firm's top management donates to Trump), CEO Republican (dummy variable equal to one if firm's top management is inclined towards the Republicans party, and zero otherwise), firm's connection to Trump, firm's competitor connection to Trump, competitor tweeted (equals one if firm's competitor is tweeted by Trump and zero otherwise) and firm's number of connection channels to Trump. One, two, and three asterisks indicate a significance level of 10%, 5%, and 1%, respectively.

	Dependent variable is all Twitter statements																	
	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)		(9)	
	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.
Size	2.215***	8.902***	1.890***	7.592***	2.227***	8.947***	1.342**	5.392***	0.793	3.185	1.650***	6.632***	1.722**	6.920***	1.917**	7.702***	2.277***	9.147***
	(4.21)	(4.24)	(3.60)	(3.61)	(4.15)	(4.18)	(2.18)	(2.19)	(1.03)	(1.04)	(2.75)	(2.76)	(2.55)	(2.58)	(2.56)	(2.58)	(4.32)	(4.31)
Lever.	0.035	0.015	-0.001	-0.000	0.035	0.015	0.052	0.022	-0.121	-.0052	0.032	0.014	-0.147	-0.063	-0.596	-0.257	0.026	0.011
	(0.31)	(0.31)	(-0.01)	(-0.01)	(0.30)	(0.30)	(0.49)	(0.49)	(-0.96)	(-0.95)	(0.30)	(0.30)	(-0.68)	(-0.68)	(-0.40)	(-0.40)	(0.17)	(0.17)
Profit.	3.126	0.260	3.719*	0.310*	3.235	0.269	2.128	0.177	-0.140	-0.011	2.650	0.221	-0.040	-0.003	1.945	0.162	4.784**	0.399**
	(1.50)	(1.51)	(1.90)	(1.92)	(1.55)	(1.56)	(1.02)	(1.03)	(-0.05)	(-0.05)	(1.25)	(1.25)	(-0.01)	(-0.01)	(0.57)	(0.57)	(2.17)	(2.19)
Altman z-score	0.135**	0.414**	0.125**	0.385**	0.136**	0.420**	0.155***	0.478***	0.138***	0.425***	0.127***	0.392***	0.117*	0.361*	0.082	0.253	0.107	0.328*
	(2.44)	(2.46)	(2.29)	(2.31)	(2.44)	(2.46)	(3.45)	(3.48)	(3.42)	(3.42)	(2.95)	(2.98)	(1.86)	(1.87)	(0.67)	(0.67)	(1.63)	(1.64)
Marg. Tax rate	-1.415	-0.136	-0.758	-0.072	-1.361	-0.130	-3.210	-0.308	-9.346	-0.899	-2.208	-0.212	-3.922	-0.377	-1.508	-0.145	-0.084	-0.008
	(-0.45)	(-0.45)	(-0.32)	(-0.32)	(-0.43)	(-0.43)	(-0.63)	(-0.63)	(-1.18)	(-1.17)	(-0.50)	(-0.50)	(-0.75)	(-0.75)	(-0.42)	(-0.42)	(-0.12)	(-0.12)
Media excl.	-1.414*	-1.286*	-1.274	-1.159	-1.441**	-1.312**	-0.828	-0.753	1.056	0.961	-0.827	-0.753	-0.289	-0.263	0.978	0.890	-0.872	-0.793
	(-1.95)	(-1.93)	(-1.64)	(-1.63)	(-1.98)	(-1.96)	(-1.23)	(-1.23)	(1.06)	(1.07)	(-1.00)	(-1.00)	(-0.37)	(-0.37)	(0.84)	(0.84)	(-1.28)	(-1.27)
Intern.	0.145	0.099	0.200	0.136	0.150	0.102	0.622	0.427	0.330	0.226	0.467	0.321	0.148	0.101	0.375	0.257	0.400	0.274
	(0.22)	(0.22)	(0.30)	(0.30)	(0.23)	(0.23)	(0.82)	(0.82)	(0.39)	(0.39)	(0.59)	(0.59)	(0.21)	(0.21)	(0.45)	(0.45)	(0.63)	(0.63)
CEO don. to Trump			1.111**	0.286**														
			(1.96)	(2.03)														
CEO Repub.					0.443	0.024												
					(0.45)	(0.46)												
Connect							2.421***	0.249***	2.746**	0.283**								
							(3.55)	(3.93)	(2.36)	(2.42)								
No. of conn. to Trump											1.447***	0.168***						
											(3.47)	(4.16)						
Compet conn. to Trump									4.100***	0.367***			3.850***	0.345***	4.128***	0.370***		
									(4.13)	(4.37)			(5.21)	(5.96)	(5.03)	(5.97)		
Compet tweeted															3.448***	0.123***	3.063***	0.109***
															(2.96)	(3.91)	(4.39)	(6.58)
No. of obs.	446		446		446		446		446		446		446		446		446	
Pseudo R^2	0.193		0.219		0.194		0.294		0.526		0.272		0.451		0.536		0.304	
Fixed effect	No		No		No		No		No		No		No		No		No	

Table 2.9.1 Logistic regression fixed effects robustness test results

The table reports coefficient estimates of logistic regression where the dependent variable is a dummy equal to one if a firm is explicitly tweeted by Trump and zero otherwise in the period from June 2015 to June 2017. Elasticity is calculated as d(ln F)/d(ln x), where d is the first derivative, ln (F) is the natural logarithm of the density function and ln (x) is the natural logarithm of the explanatory variable and is evaluated at the sample means of the explanatory variables. In addition to the control variables which include company size (log of total assets), leverage (total debt to total capital), profitability (return on assets), Altman z-score (likelihood of bankruptcy), marginal tax rate (the amount of tax paid on an additional dollar of income) and media excluding (control for non-media company effect), I control for company internationalization (change of foreign assets as a % of total assets in the tweeting period), CEO donation to Trump (whether firm's top management donates to Trump), CEO Republican (dummy variable equal to one if firm's top management is inclined towards the Republicans party, and zero otherwise), firm's connection to Trump, firm's competitor connection to Trump, competitor tweeted (equals one if firm's competitor is tweeted by Trump and zero otherwise) and firm's number of connection channels to Trump. One, two, and three asterisks indicate a significance level of 10%, 5%, and 1%, respectively.

	Dependent variable is all Twitter statements																	
	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)		(9)	
	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.	Coeff.	Elast.
Size	2.427***	9.845***	2.056***	8.322***	2.425***	9.835***	1.469**	5.934**	0.793	3.185	1.783***	7.228***	2.637**	10.726**	2.473**	10.012**	2.414***	9.775***
	(3.80)	(3.76)	(3.23)	(3.21)	(3.82)	(3.78)	(2.17)	(2.17)	(1.22)	(1.22)	(2.70)	(2.70)	(2.27)	(2.24)	(2.43)	(2.42)	(3.63)	(3.61)
Lever.	0.035	0.015	-0.003	-0.001	0.035	0.015	0.051	0.022	-0.121	-0.052	0.035	0.015	-0.184	-0.080	-0.859	-0.374	0.014	0.006
	(0.11)	(0.11)	(-0.01)	(-0.01)	(0.11)	(0.11)	(0.16)	(0.16)	(-0.32)	(-0.32)	(0.11)	(0.11)	(-0.31)	(-0.31)	(-0.49)	(-0.49)	(0.03)	(0.03)
Profit.	2.817	0.238	3.517	0.296	2.932	0.247	1.772	0.149	-0.140	-0.011	2.048	0.172	-1.309	-0.110	1.853	0.155	4.603	0.388
	(0.76)	(0.76)	(0.96)	(0.97)	(0.79)	(0.79)	(0.46)	(0.46)	(-0.03)	(-0.03)	(0.52)	(0.52)	(-0.24)	(-0.24)	(0.29)	(0.29)	(1.19)	(1.20)
Altman z-score	0.139*	0.433*	0.131	0.406	0.140*	0.436*	0.164**	0.507**	0.138	0.425*	0.142*	0.441**	0.194	0.602	0.133	0.412	0.102	0.316
	(1.69)	(1.71)	(1.54)	(1.55)	(1.70)	(1.72)	(2.24)	(2.28)	(1.63)	(1.65)	(1.94)	(1.97)	(1.22)	(1.22)	(0.65)	(0.66)	(0.94)	(0.95)
Marg. Tax rate	-0.779	-0.075	-0.380	-0.036	-0.761	-0.073	-2.594	-0.249	-9.346*	-0.899*	-1.381	-0.133	-1.403	-0.134	-0.673	-0.064	-0.005	-0.000
	(-0.24)	(-0.24)	(-0.14)	(-0.14)	(-0.23)	(-0.23)	(-0.57)	(-0.57)	(-1.93)	(-1.92)	(-0.33)	(-0.33)	(-0.40)	(-0.40)	(-0.28)	(-0.28)	(-0.01)	(-0.01)
Media excl.	-1.494*	-1.371*	-1.353*	-1.239*	-1.514*	-1.389*	-0.876	-0.801	1.056	0.961	-0.914	-0.838	-0.270	-0.248	0.999	0.916	-0.959	-0.879
	(-1.90)	(-1.88)	(-1.69)	(-1.68)	(-1.92)	(-1.90)	(-1.09)	(-1.08)	(1.06)	(1.07)	(-1.07)	(-1.07)	(-0.21)	(-0.21)	(0.71)	(0.72)	(-1.05)	(-1.04)
Intern.	0.162	0.112	0.202	0.139	0.164	0.113	0.651	0.448	0.330	0.226	0.499	0.345	0.072	0.050	0.478	0.330	0.436	0.301
	(0.25)	(0.26)	(0.31)	(0.33)	(0.25)	(0.26)	(0.93)	(0.94)	(0.39)	(0.39)	(0.70)	(0.71)	(0.07)	(0.08)	(0.47)	(0.47)	(0.63)	(0.62)
CEO don. to Trump			1.114**	0.291**														
			(2.01)	(2.06)														
CEO Repub.					0.351	0.019												
					(0.30)	(0.31)												
Connect							2.503***	0.263***	2.746***	0.283***								
							(3.75)	(3.98)	(3.24)	(3.50)								
No. of conn. to Trump											1.611***	0.191***						
											(3.26)	(3.57)						
Compet conn. to Trump									4.100***	0.367***			5.120***		5.107***	0.475***		
									(4.92)	(5.43)			(2.87)		(3.34)	(3.21)		
Compet tweeted															4.250***	0.155***	3.449***	0.123***
															(2.89)	(3.18)	(3.63)	(4.96)
No. of obs.	446		446		446		446		446		446		446		446		446	
Pseudo R^2	0.169		0.219		0.178		0.259		0.138		0.168		0.193		0.198		0.190	
Fixed effect	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	

2.8.2 Cross-sectional regression robustness test results

Table 2.10 and Table 2.10.1 present the robustness test results from the cross-sectional regression analysis. In addition, Table 2.10.1 present the estimates including industry fixed effects. The coefficient in front of the "CEO donation to Trump" in which certain company's top management is related to Trump through donations, suggests rather positive impact on the CARs of about 1.164% (see, event window [0, 5]) of a return benefit. Furthermore, the results show positive and statistically significant at 1% level impact on the CARs when companies' top management is politically-inclined towards the Republican party. Apart from the business and political connection variables, the analysis in Table 2.10 further incorporates linguistic tone control variable as well as an interaction term between the tone and the connection variable. However, I find no statistically significant evidence for the resulting estimates. Overall, these results provide fair robustness evidence of the previously obtained results.

2.9 Concluding remarks

In this chapter, I focus on Trump's public statements around the 2016 U.S. presidential elections and I observe their effects on the stock market outcomes. The chapter makes new contributions to the existing literature on the relationship of companies' exposure to presidential candidate's notions and remarks in the media, companies' top management political orientation and business connections to the presidential candidate, and investors' sentiment provoked by the presidential candidate's disseminated information to the public. Using a sample of NYSE and Nasdaq listed companies, my study shows evidence that Trump is more likely to cover in his statements the companies with which he had an established business and political connection, companies of large size, and companies with presence on the international markets.

Furthermore, I find that the isolated effect from Trump's statements is not of vital economic importance for companies' value, however it is statistically significant upon the stock returns of the companies that he explicitly mentions. In addition, I find that the negative linguistic tone carried in his statements negatively contributes to companies' cumulative abnormal returns.

Finally, I observe evidence that companies' political orientation and business connection to President Trump and his family has some influence on companies' stock returns, trading volume, and stock price volatility.

To sum up, the findings in this chapter suggest that through their public statements and close connections to the companies of the business sector, government officials can influence investor expectations and, in turn stock market outcomes. The findings of this chapter should not be viewed as commentary on Trump's actions, rather, I solely document the market's reaction to his public statements.

Table 2.10 Cross-sectional regression robustness test results

The table reports coefficient estimates of OLS regressions of cumulative average abnormal returns (CARs), abnormal trading volume (AV) and volatility around Trump's statements in the period from June 2015 to June 2017. Each announcement date is considered as an event day (t=0). Abnormal returns are calculated using the one-factor market model $r_{i,t} = \alpha_0 + \beta_1 r_{m,t} + \varepsilon_t$, where $r_{i,t}$ is the return on stock i in period t and $r_{m,t}$ is the S&P 500 return, is estimated using a 250-day estimation window over [0,5], [0,0] and [0,1] event windows. Abnormal trading volume is calculated as the difference between the trading volume $V_{i,t}$ and mean trading volume of the previous seven days divided by the mean trading volume of the previous seven days. Volatility is calculated as $\hat{\sigma}_{it}{}^2 = (H_{it} - C_{it})(H_{it} - O_{it}) + (L_{it} - C_{it})(L_{it} - O_{it})$ where O_{it}, C_{it}, H_{it} and L_{it} are the natural log of the opening, closing, high and low prices for company $\boldsymbol{i}$ on day $\boldsymbol{t}$, respectively. Control variables include company size (log of total assets), leverage (total debt to total capital), profitability (return on assets), Altman z-score (likelihood of bankruptcy), and media excl. (control for non-media company effect). Columns (6) – (10) consider industry fixed effects. One, two, and three asterisks indicate a significance level of 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Dependent variable is CAR [0,5]	Dependent variable is CAR [0,5]	Dependent variable is CAR [0,0]	Dependent variable is CAR [0,0]	Dependent variable is CAR [0,1]	Dependent variable is CAR [0,1]	Dependent variable is AV	Dependent variable is AV	Dependent variable is volatility	Dependent variable is volatility
Size	-0.049 (-0.22)	-0.047 (-0.22)	0.072 (0.67)	0.041 (0.38)	0.336** (2.42)	0.334** (2.34)	0.260*** (3.43)	0.286*** (3.58)	-0.215*** (-3.05)	-0.218*** (-2.96)
Leverage	0.912 (1.62)	0.894 (1.56)	0.595 (1.54)	0.588 (1.63)	1.095*** (2.75)	1.069*** (2.79)	0.382 (0.89)	0.401 (1.00)	0.148 (0.69)	0.148 (0.68)
Profitability	-0.015 (-0.43)	-0.019 (-0.62)	-0.031** (-2.05)	-0.032** (-2.13)	-0.034* (-1.77)	-0.036* (-1.84)	-0.010 (-0.94)	-0.009 (-0.88)	-0.020** (-2.22)	-0.020** (-2.27)
Altman z-score	-0.096*** (-3.15)	-0.075** (-2.05)	-0.006 (-0.39)	-0.006 (-0.41)	-0.035** (-2.24)	-0.027 (-1.52)	0.037** (2.03)	0.039*** (2.64)	0.018** (1.98)	0.019** (2.02)
Media excl.	-1.003** (-1.97)	-1.131** (-2.28)	-0.601** (-2.14)	-0.757*** (-2.95)	-0.761*** (-2.53)	-0.812*** (-2.79)	0.380** (2.16)	0.596*** (2.76)	0.474*** (3.05)	0.463*** (2.97)
Connect	0.631 (0.68)	0.163 (0.17)	0.203 (0.37)	0.145 (0.30)	0.340 (0.48)	0.641 (0.94)	-0.252 (-0.69)	-0.176 (-0.47)	0.006 (0.02)	0.007 (0.02)
Negative	-0.358 (-0.50)	-0.724 (-1.05)	-0.367 (-1.37)	-0.253 (-1.04)	-0.458 (-0.85)	-0.592 (-1.12)	0.004 (0.02)	-0.120 (-0.56)	-0.037 (-0.18)	-0.029 (-0.13)
Connect _Negative	-0.261 (-0.30)	-0.163 (-0.29)	-0.241 (-0.60)	-0.169 (-0.47)	-0.360 (-0.53)	-0.170 (-0.26)	0.227 (0.72)	0.180 (0.60)	-0.106 (-0.42)	-0.101 (-0.40)
CEO donation to Trump		1.164** (2.25)		0.326 (1.12)		0.456 (1.25)		-0.378 (-1.19)		0.036 (0.19)
CEO Republican		2.460*** (2.92)		0.518 (1.19)		0.907* (1.74)		-0.531* (-1.86)		0.032 (0.15)
CEO Democrat		-0.565 (-1.47)		0.149 (0.45)		-0.172 (-0.56)		0.133 (0.54)		0.033 (0.22)
Number of obs.	274	274	274	274	274	274	274	274	274	274
R-squared	0.384	0.125	0.114	0.150	0.112	0.129	0.318	0.371	0.229	0.230
Fixed effect	No	No	No	No	No	No	No	No	No	No

Table 2.10.1 Cross-sectional regression fixed effects robustness test results

The table reports coefficient estimates of OLS regressions of cumulative average abnormal returns (CARs), abnormal trading volume (AV) and volatility around Trump's statements in the period from June 2015 to June 2017. Each announcement date is considered as an event day (t=0). Abnormal returns are calculated using the one-factor market model $r_{i,t} = \alpha_0 + \beta_1 r_{m,t} + \varepsilon_t$, where $r_{i,t}$ is the return on stock i in period t and $r_{m,t}$ is the S&P 500 return, is estimated using a 250-day estimation window over [0,5], [0,0] and [0,1] event windows. Abnormal trading volume is calculated as the difference between the trading volume $V_{i,t}$ and mean trading volume of the previous seven days divided by the mean trading volume of the previous seven days. Volatility is calculated as $\hat{\sigma}_{it}{}^2 = (H_{it} - C_{it})(H_{it} - O_{it}) + (L_{it} - C_{it})(L_{it} - O_{it})$ where O_{it}, C_{it}, H_{it} and L_{it} are the natural log of the opening, closing, high and low prices for company i on day t, respectively. Control variables include company size (log of total assets), leverage (total debt to total capital), profitability (return on assets), Altman z-score (likelihood of bankruptcy), and media excl. (control for non-media company effect). Columns (6) – (10) consider industry fixed effects. One, two, and three asterisks indicate a significance level of 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Dependent variable is CAR [0,5]	Dependent variable is CAR [0,5]	Dependent variable is CAR [0,0]	Dependent variable is CAR [0,0]	Dependent variable is CAR [0,1]	Dependent variable is CAR [0,1]	Dependent variable is AV	Dependent variable is AV	Dependent variable is volatility	Dependent variable is volatility
Size	-0.062 (-0.18)	-0.089 (-0.22)	0.086 (0.44)	0.051 (0.21)	0.490*** (2.64)	0.491** (2.28)	0.038 (0.26)	0.021 (0.17)	-0.289*** (-3.45)	-0.292*** (-3.03)
Leverage	0.788 (0.47)	0.570 (0.38)	0.450 (0.79)	-0.346 (-0.54)	1.247 (1.17)	1.274 (1.12)	1.433* (1.81)	1.547** (2.37)	0.207 (0.75)	0.224 (0.89)
Profitability	-0.068 (-1.14)	-0.073 (-1.24)	-0.021 (-1.03)	-0.024 (-1.06)	-0.044* (-1.86)	-0.047* (-1.64)	0.008 (0.38)	0.001 (0.07)	-0.009 (-0.42)	-0.009 (-0.47)
Altman z-score	-0.011 (-0.13)	-0.015 (-0.20)	-0.060 (-1.49)	-0.042 (-1.32)	-0.022 (-0.42)	-0.019 (-0.35)	0.091*** (2.67)	0.108*** (3.27)	-0.007 (-0.30)	0.005 (0.20)
Media excl.	-0.784 (-0.65)	-0.677 (-0.69)	-1.905** (-2.13)	-1.609*** (-2.53)	-0.209 (-0.26)	0.075 (0.09)	0.026 (0.03)	0.702 (0.94)	-0.349 (-1.15)	0.272 (0.68)
Connect	0.306 (0.28)	0.140 (0.13)	0.163 (0.21)	0.130 (0.16)	0.971 (1.34)	0.947 (1.30)	-0.843*** (-3.53)	-1.100*** (-3.61)	-0.240 (-0.65)	0.283 (0.87)
Negative	-1.633** (-2.43)	-1.761** (-2.35)	-0.366 (-1.32)	-0.319 (-0.97)	-0.792 (-1.52)	-0.770 (-1.43)	0.120 (0.68)	0.137 (1.07)	0.160 (0.56)	-0.167 (-0.56)
Connect _Negative	-1.144 (-1.48)	-1.252* (-1.80)	-0.365 (-1.16)	-0.316 (-0.88)	-0.271 (-0.35)	-0.225 (-0.29)	0.035 (0.17)	0.182 (0.63)	-0.074 (-0.23)	-0.063 (-0.19)
CEO donation to Trump		0.878 (1.00)		0.758** (2.42)		0.142 (0.24)		-0.806* (-1.67)		0.123 (0.52)
CEO Republican		1.216 (1.32)		0.175 (0.41)		0.473 (0.51)		-0.653* (-1.81)		0.044 (0.07)
CEO Democrat		-1.016* (-1.78)		0.463* (1.70)		-0.148 (-0.36)		0.542 (1.54)		0.073 (0.34)
Number of obs.	274	274	274	274	274	274	274	274	274	274
R-squared	0.336	0.348	0.658	0.692	0.351	0.353	0.677	0.636	0.435	0.436
Fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

3 NUCLEAR ACCIDENTS IMPACT ON THE FINANCIAL MARKETS[♣]

3.1 Overview

This chapter studies whether nuclear accidents in the period from 1944 to 2017 have a significant impact on the U.S. publicly listed companies. I study whether the geographic proximity of information disseminated by the nuclear accident events affect stock prices in the U.S. I find that nuclear accidents effect is negative upon the companies when the accidents take place on U.S. soil. This result suggests that the information disseminated from the nuclear accidents is more relevant for the companies that are geographically closer to both the birthplace of the accident and the financial markets. Additional tests also show that the effect differs across company size, across company industry, and is followed by perceived risk surge; that is, the implied volatility increases after the nuclear accident events. I further differentiate between two channels through which the nuclear accidents influence the financial markets. I find evidence that through the "fear channel" the influence of the accidents trigger fear among the investors which then contributes to depressed stock prices.

3.2 Introduction

Around four o'clock in the afternoon on 11 March 2011 a 14-meter tsunami hit the protective seawall of the Fukushima Daiichi nuclear plant. The sequence of natural events i.e. the earthquake first and tsunami later, claimed the lives of three workers of the nuclear power plant and affected nearly 16,000 lives of people living in the region. More than 100,000 people were forced to evacuation, whereas the Fukushima Daiichi nuclear plant is still a subject of a large refurbishment and a clean-up project estimated to cost $100bn. Following the situation in Japan, the German Chancellor Angela Merkel ordered an immediate shutdown on almost half of Germany's nuclear plants. This economically important reaction marked yet another change in Germany's nuclear power policy but this time, however, the change came unexpectedly fast and with no change of the government.

A relatively large body of literature examines events of nature, such as disasters, that evoke "bad mood" and anxiety among the public and especially financial investors. Anxiety is shown to drive investor sentiment against taking risks, it contributes to pessimism regarding future returns and thus dictates asset price movements (see for e.g. Baker and Wurgler, 2007; Lucey and Dowling, 2005). Early studies discover, for example, that the weather, which is a well-known driver of peoples' mood, tends to positively commove with daily stock returns (Hirshleifer and Shumway, 2003). In a more recent study, Kaplanski and Levy (2010b) study the impact of aviation disasters on investor sentiment. They find that aviation disasters negatively affect investor sentiment and temporarily increase the fear for trading. In another

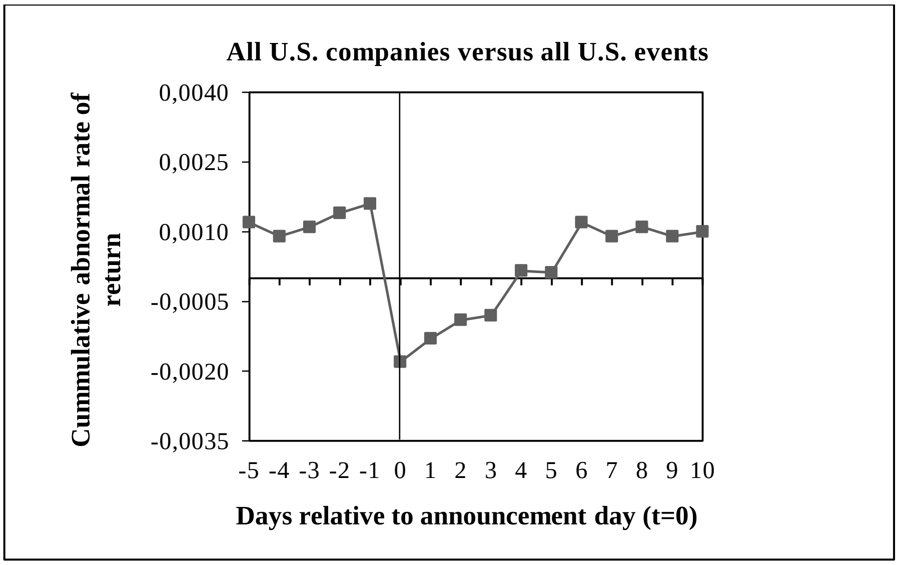
[♣] This chapter is co-authored with Matej Marinč.

study, Yuen and Lee (2003) study risk-taking predispositions in various mood states. They show that people in a depressed mood have lower willingness to engage themselves in risky situations than people in positive or neutral mood states.

I investigate the 1944–2017 nuclear accident events taking place in the U.S. (reported by the U.S. Department of Defense), in Japan, and in France (both reported in the U.S. newspaper outlets) and I examine the accidents' impact on the U.S. stock returns. I differentiate between two channels through which the nuclear accidents influence the financial markets. The "economic channel" is the channel through which nuclear accidents if they happen on a large scale would trigger economic losses and such losses would result in lower stock prices. The "fear channel" is the channel through which nuclear accidents trigger fear among the investors and that translates to depressed stock prices.

As a preliminary exploration, I plot companies CARs around the nuclear accident event days – for the accidents taking place on U.S. soil, in Figure 3.1. I find negative CARs on the event days – for a 16-day event window, and a stock return reversal pattern on the day following the accident days. A possible reason for the reversal pattern may be that investors in fear act irrationally to the news on the nuclear accident and after one day they stabilize their behavior.

Figure 3.1 Cumulative Abnormal Rate of Return (CAR)



Notes. The figure depicts the nuclear accidents effect surrounding the event day (t=0) proxied by the CARs calculated using the market model for the sample of companies listed on the NYSE Composite and NASDAQ Composite. The events occurred from 1944 to 2017. The effect presented in the figure is based on a preliminary evaluation and it does not account for overlapping among the events' windows.

I start by evaluating whether the geographic proximity of the information from the nuclear accidents to the financial markets has a statistically significant impact on the U.S. companies stock prices. Motivated by the previous studies such as Ichev and Marinč, (2017) and Engelberg and Parsons (2011), I expect that the nuclear accident events unequally affect investors' sentiment about stock returns—depending on investors' distance to the nuclear energy accidents from the markets.

The sample of companies consists of all NYSE Composite and NASDAQ Composite. I also distinguish among the nuclear accidents depending on where they occur (i.e., in the U.S., Japan, or Europe). I find that the stock price reaction is negative, significant, and the strongest in absolute terms when a nuclear accident takes place in the U.S. This result suggests that the information about the nuclear energy accidents is more relevant for companies that are geographically closer to both the birthplace of the accidents and the financial markets.

Second, I observe whether there is a difference in the magnitude of the effect upon the companies' returns when classified in ten different capitalization sizes. I find some evidence that the negative stock price reaction is more pronounced for the stocks in decile 10, i.e., small cap stocks, relative to the companies in decile 1, i.e., large cap stocks. A potential explanation for this effect is that information dissemination may be less effective for small cap stocks compared to large cap stocks.

Third, I investigate the magnitude of the effect from the nuclear accident events for securities belonging to a specific industry. I find evidence that the event effect differs among different industries and is of a benefit for the clean energy industry.

Next, I proxy investor sentiment through the implied volatility and I investigate whether that the nuclear accident events affect the implied volatility on the day of the accident. I find that implied volatility increases on the nuclear accident days but then abates—pointing to a mood-driven effect.

Lastly, I investigate whether the nuclear accidents trigger fear among the investors that would later translate to depressed stock prices. I find that small firms which are located outside of the state where the nuclear accident occurred were affected more than the large firms in the state where the nuclear disaster occurred, suggesting that presence of fear is widely expressed among the financial markets' investors around the nuclear accidents.

This chapter makes the following contributions. To the extent of my knowledge, this study is among the first to collect a large time-span (from the year 1944 to 2017) of nuclear energy accidents, and to evaluate the impact of the nuclear energy accident events on the financial markets with the intent to analyze information dissemination in combination with the proximity of the event. Regarding literature examining the effect of investor sentiment on the financial markets, my study is closely related to Kaplanski and Levy (2010a, 2010b) and Donadelli et al. (2016a) and shed light on the role of geographic proximity of information to the financial markets and its effects on investors' decision making process. My results reveal evidence that there is a clear relation between nuclear accident events and investors' actions and the magnitude of the event effect.

Furthermore, I contribute to the literature observing the effects of media coverage on investor sentiment, by considering the geographic proximity of the information to the financial markets. My findings relate to Engelberg and Parsons (2011), Peress (2014), and Donadelli (2015) who find that investors react more to media covered events and pay more attention to stocks and news/events that are closer in distance to them, as well as to the events that trigger fear among the investors.

The remainder of the chapter goes as follows. Section 3.3 provides a theoretical background. Section 3.4 describes the data. Section 3.5 reveals the methodology and delineates the hypotheses tested in this study. Section 3.6 presents the results. Section 3.7 concludes the chapter.

3.3 Theoretical Background

This study is related to the strands of literature observing relations between: firm exposure to events taking place in different geographic regions, firm size and type of industry in which they operate, and investor sentiment as a result of the nuclear accident events.

Several studies in the existing literature focus on the consequences of nuclear accidents on stock prices. Bowen et al. (1983) study the effect of Three Mile Island (TMI) accident on the U.S. utility stock returns. They find negative and statistically significant abnormal returns for firms with current or planned nuclear realizations as well as a long-run upward shift in both residual and market risk. In addition, they find that firms with high nuclear commitments exhibit larger declines in equity prices than firms from the non-nuclear sector.

Fields and Janjigian (1989) study the U.S. public electric utility stock price reaction to the Chernobyl nuclear plant disaster. They find negative daily abnormal returns for all firms. In addition, Kalra et al. (1993) observe whether daily stock returns of U.S. electric utilities reacted to the Chernobyl nuclear catastrophe by grouping the firms by their nuclear capacity. They find negative stock return reactions on the Chernobyl accident for all firms, however the mixed group of firms with a nuclear capacity of 10%--20% are the ones with the worst performance.

Aktar (2005) compares the Chernobyl nuclear accident with the TMI accident and their impact on the equity prices of U.S. electric utilities. He observes a relatively greater impact on three types of firms: firms with a larger degree of nuclear exposure after the Chernobyl accident, firms already experiencing problems with the Nuclear Regulatory Commission, and firms with nuclear power plants under construction.

Another strain of literature that my study is related to identifies a relationship between the media as an information disseminator and investor sentiment. Blendon et al. (2004) study the media coverage of the Severe Acute Respiratory Syndrome (SARS) disease outbreak. They find that the media tends to extensively cover rare events, new events, and dramatic events.

Hence, as shown by Kepplinger and Hans Mathias (2008), when an unusual event occurs, the media starts hunting "newer" news on the same specific topic which further affects investor sentiment.

Within similar lines, this chapter is related to Kaplanski and Levy (2010b) who study the impact of aviation disasters on investor sentiment. They show that aviation disasters negatively affect investor sentiment and increase the fear for trading few days after the event. In addition, several studies that analyze securities' implied volatility, investors' trading behavior and risk taking attitude confirm the fact that fear and anxiety, are positively related to investors' risk aversion (see, Baker and Wurgler, 2007; Mehra and Sah, 2002; Hanock, 2002). Alongside, Donadelli et al. (2016b) examine whether the fear index - as a proxy for investor mood, driven by various dangerous diseases is priced in pharmaceutical companies' stocks. They find positive effect upon pharmaceutical companies' stocks and argue that events such as global diseases should not trigger rational trading.

My study is also related to Francis et al. (2007) and Engelberg and Parsons (2011) who examine the role of a geographic location on an investor behavior and a firm decision-making process. Francis et al. (2007) find that geographic proximity affects the dissemination of information and thus the financial markets. Geographically remote firms (usually rural firms) exhibit higher costs of debt than the firms located in the urban areas. In their study, Ichev and Marinč (2017) show that the information on the events is more relevant for companies that are geographically closer to both the birthplace of the events and the financial markets. They also show that the effect is more pronounced for small and more volatile stocks, stocks of specific industry, and for the stocks exposed to intense media coverage.

3.4 Data

3.4.1 Nuclear Accidents

The data examined cover the mass-media circulated nuclear accident events in the period from 1944 to 2017. The U.S. Department of Defense defines "nuclear accidents" as "unexpected events involving nuclear material, weapons or nuclear weapons components that result in any of the following: accidental or unauthorized launching, firing or use, by U.S. Forces or supported allied forces of a nuclear-capable weapon system which could create the risk of an outbreak of war; nuclear detonation; non-nuclear detonation or burning of a nuclear weapon or radioactive weapon component - including a fully assembled nuclear weapon, an unassembled nuclear weapon, or a radioactive nuclear weapon component; radioactive contamination; seizure, theft, or loss of a nuclear weapon or radioactive nuclear weapon component - including jettisoning; public hazard - actual or implied".

The entire period incorporates 102 nuclear accidents - which I consider to be the event days i.e. *events*, taking place on U.S. territory (87 events), in France (7 events), and in Japan (8 events). I choose these event locations due to the credibility of the source of the data. For example, it would be interesting to observe nuclear accident events from countries that are perceived to be heavily inclined towards using nuclear energy or at least having nuclear programs, like Russia, North Korea, Iran etc., however I find no credible source to confirm the day, time and place of the nuclear accident - especially the accidents involving military weapons.

I collect the events from two sources: the "U.S. newspaper outlets", and the "U.S. Department of Defense". The U.S. newspaper outlets events are obtained from the LexisNexis article search engine. To retrieve the nuclear accident news from the LexisNexis, I use the search term "nuclear accidents and tests". In addition, I set the engine to browse the three largest U.S. newspapers by circulation (The New York Times, The Washington Post and The Wall Street Journal) reporting on the events.[24]

The U.S. Department of Defense events that I consider are official statements communicated to the public with regard to any information related to a nuclear accident. For example, on April 2, 1962, the U.S. Department of Defense reported that an "unplanned nuclear excursion occurred in a plutonium processing facility in Richland, Washington. Several employees were hospitalized due to exposure to the resultant radiation, and radiation was detected in the surrounding atmosphere for several days following the incident".

Although the events I consider do not occur on a daily or weekly basis (in most of the cases), I consider the fact that regularly spaced updates may be anticipated by the financial investors and thus priced preceding the actual update. For this reason, the sample of accidents considers only those updates documenting a news-event for the first time. For example, The U.S. Department of Defense reports the accident on the day that the accident happens, while the media reports on the accident several days after the occurrence of the accident. Since the primary source of data is the media, I set the event days to be the days when nuclear accidents first appear in the media. Another reason to choose the events as they are broadcasted in the media is that some nuclear accidents, especially the ones that occurred during the Cold War period, are only recorded and disseminated by the media, whereas in reality the exact day and time of occurrence of the accident is considered as just a speculation. Such a strategy helps to ensure the independence of subsequent as well as sequential updates. All announcements are categorized and summarized in Table C.2.

3.4.2 Stock Market Data

To examine whether the geographic proximity of information to the financial markets has an impact on companies' stock returns as a result of the accidents, I employ the value-weighted total returns (see Table C.1 for definition) from the Center for Research in Security Prices

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[24] Updated September 29, 2017, both printed and online coverage is considered: www.cision.com/us/2014/06/top-10-us-daily-newspapers/.

(CRSP) of the New York Stock Exchange (NYSE) and NASDAQ Composite listed companies. I use the S&P500 index as a market performance benchmark.

The NYSE Composite and Nasdaq Composite primarily contain large stocks which are generally characterized by good information dissemination and in good portion reflect the U.S. economy. Both markets were chosen for two reasons. First, they are the most closely followed in the world, hence very efficient with respect to dissemination of new information (Kaplanski and Levy, 2010a, 2010b). Second, the U.S. stock markets are among the leading stock markets in the world and account for almost 50% of the global market (Hou et al., 2011). I further use Bloomberg database to build the portfolios of companies which are listed on the U.S. stock markets (NYSE and NASDAQ) and have exposure to the events in the sample. To ensure unbiased selection of the companies, I use the following three-step procedure. First, I select the companies by status: I am interested in "active and publicly listed" companies on the U.S. financial markets. Second, I further select the companies that have a domicile in the U.S. as well as I record in which U.S. state they are exactly located, and third, I set up the "period of operation" of the companies from 1944 to June 2017.

To further analyze a potential differential effect regarding the company size, I employ Fama and French's (1993) 10 value-weighted portfolios constructed by size, obtained from the CRSP.

To analyze events' effect upon the industry in which a certain company operates, I use a portfolio created by selecting the 11 largest industries by contribution to the U.S. GDP in the period from 1944 to 2017. Industry data is acquired from the S&P Dow Jones Industry Index.

To examine investor sentiment, I follow Whaley (2009) and I use Chicago Board of Options Exchange's VIX and VXO[25] indices that serve as proxies for investor sentiment.

Lastly, to observe existence of fear channeling between the U.S. companies and the nuclear accident events that may trigger investor sentiment and thus affect stocks' returns, I match each event and company location across the U.S. states. For each event location across the U.S. I consult the U.S. Department of Defense database and for each company location I browse the Standard & Poor's 500 company list from Bloomberg database.

3.5 Methodology and Hypotheses

I distinguish between two channels through which the nuclear accidents influence the financial markets. The first, I call it an "economic channel", is the channel through which a nuclear accident if it happens on a large scale would trigger economic losses and such losses (or merely investors anticipating such losses) would result in depressed stock prices. The second, I call it a "fear channel", is the channel through which a nuclear accident triggers fear

[25] Retrieved from the website: www.cboe.com.

and anxiety among the investors and that results in depressed stock prices. I use two sets of methodology to evaluate the impact of the nuclear accidents on the stock returns as well as to disentangle the impact among the two channels of influence. The event-study methodology is exercised to evaluate the economic impact of the accidents upon companies' stock returns through the one-factor market model, as inspired by prior research (e.g. Donadelli et al., 2016; Peress, 2014; Fang and Peress, 2009)[26]. The one-factor model is estimated as:

$$r_{i,t} = \alpha_0 + \beta_1 r_{m,t} + \varepsilon_t \tag{1}$$

where $r_{i,t}$ is the rate of return on stock i in period t and $r_{m,t}$ is the S&P500 rate of return, which acts as a market portfolio proxy.

I start by computing the cumulative average abnormal returns (CARs) around the events considered. The abnormal returns (ARs) are defined as the difference between the actual rate of return of the stock considered and its ex-post expected rate of return over the whole length of the event window. I position 250 trading days in the estimation period ending 30 days prior to the accident day, i.e. day 0, and I estimate four event windows: [-5, 5], [0, 5], [0, 10], and [0, 20] (for examples of event study designs, see MacKinlay, 1997[27]).

The sample of nuclear accident events that I consider is temporally clustered. The event study results would suffer from noise in the data because of the overlapping windows if all events were considered. For this reason, I use only nuclear accident events with non-overlapping event windows. I use the following criteria to select events. The selection criterion which I label as "the first occurrence" selects events in chronological order (sequence). It starts with the first event in the sample, ignores all events showing up in the following 6, 11, or 21 days - depending on the length of the event window ([-5, 5], [0, 5], [0, 10], and [0, 20]), takes the next event in succession, ignores the following 6, 11, or 21 days, and so on until the whole sample is exhausted. In a more illustrative way, assume there are five events taking place on dates g_0, g_1, g_2, g_3, and g_4 where g_1, g_2, and g_3 are temporally clustered. In this case, "first occurrence" uses events for CAR calculation taking place on days g_0, g_1, and g_4. With this strategy, I avoid unintentional bunching of events with overlapping windows in the same basket. In addition, following Foster (1980) and Kaplanski and Levy (2010b) the events are also examined as being mutually exlclusive - meaning that it is assumed that there is no other major macroeconomic event on the same date that might affect the exact sample of companies that is observed in this study.

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[26] In addition, robustness inference would encounter a two-factor market model too. The two-factor market model - $r_{i,t} = \alpha_0 + \beta_1 r_{m,t} + \beta_2 r_{ind,t} + \varepsilon_t$, where $r_{i,t}$ is the rate return on stock i in period t, $r_{m,t}$ is the S&P500 rate of return, and $r_{ind,t}$ is the industry specific rate of return, is rather beneficial in event studies with limited/short time-span data (low number of events, short time between events), and during high stock price volatility and trading volume in the market because of unknown or unobservable reasons (MacKinlay, 1997; Fang and Peress, 2009).

[27] MacKinlay (1997) concludes that, as long as the event windows among the selected events are not overlapping, there is no strict rule about the size of the event window, hence symmetrical distribution of the days surrounding the main event day would imply simpler and faster computation.

To observe whether the proximity of information from the three event locations significantly affects U.S. companies stock returns as well as to observe a potential reversal pattern (driven by positive/negative sentiments), company size and industry effects, I run the following regression model (see, e.g. Kaplanski and Levy, 2010a, 2010b; Kamstra, Kramer et al., 2003; Brown and Warner, 1985):

$$r_{i,t} = \gamma_0 + \sum_{j=1}^{3} \gamma_{1,i} r_{i,t-j} + \sum_{k=1}^{4} \gamma_{2,k} WD_{k,t} + \gamma_3 Tax_t + \sum_{l=0}^{4} \gamma_{4,l} E_{l,t} + \epsilon_t, \qquad (2)$$

where $r_{i,t}$ is the rate of return of stock i on day t, γ_0 is the regression intercept, $r_{i,t-j}$ is the lagged dependent variable—the jth previous day rate of return, $WD_{k,t}$ with $k = 1, \dots, 4$ are dummy variables for the day of the week (Monday, Tuesday, Wednesday, and Thursday), Tax_t is a dummy variable for the first five days of the taxation year, and finally, $E_{l,t}$ with $l = 0 \dots 4$, stands for possible event effect and reversal effect indicator. Regression's standard errors are clustered by firm (using their CUSIP - Committee on Uniform Securities Identification Procedures code).

The reason for including rates of return in previous days, $r_{i,t-j}$ in the regression in (2) is a potential presence of a serial correlation. A serial correlation is one of the known anomalies that may contaminate the results and may occur as a result of time-varying expected returns, non-synchronous trading, or transaction costs (see, e.g., Schwert 1990a, 1990b, 2003; Campbell et al., 1993). I look at as many previous days' returns as is necessary to ensure that all significant correlations have been accounted for. In my case, it is the rates of return of the first three previous days. Following French (1980), Schwert (1990a), and Cho et al. (2007), I also acknowledge that the events may not be evenly distributed over the week either by the coincidence or by the nature of the events. I use dummies for each day of the week, WD_{it}, to capture the so-called "Monday effects" or "weekend effect."[28] Lastly, I add a dummy for the first five days of the taxation year, Tax_t, starting at January 1st, to account for the so-called "turn-of-the-year effect" (see, e.g., Chien and Chen, 2008).[29]

To observe whether nuclear accidents influence the financial markets through the fear channel, I run the following two regression models:

$$r_{i,t} = \gamma_0 + \gamma_1 Small\_Close_i + \gamma_2 Big\_Far_i + \gamma_3 Small\_Far_i + \gamma_4 E_{t,0} + \gamma_5 interactions_i + \gamma_6 controls_i + \epsilon_t, \qquad (3)$$

where $r_{i,t}$ is the rate of return of stock i on day t for all U.S. firms, U.S. nuclear energy firms and U.S. clean energy firms respectively, $Small\_Close_i$ is a dummy variable equal to 1 if stock i is small (i.e. belongs to deciles 6-10) and it is in the same state in which the nuclear accident occurs, and zero otherwise. Big_Far_i is a dummy variable equal to 1 if stock i is large (i.e. belongs to deciles 1-5) and it is not in the same state in which the nuclear accident

[28] The "Monday" or "weekend effects" anomaly captures the market returns' trend on Monday following the trend from last Friday. For more on this effect, see Cho et al. (2007).
[29] The "turn-of-the-year effect" is an anomaly higher stock prices and trading volume at the of December and the first two weeks of January (see, e.g., Chien and Chen, 2008).

occurs, $Small\_Far_i$ is a dummy variable equal to 1 if stock i is small and it is not in the same state in which the nuclear accident occurs, and $E_{t,0}$, stands for possible event effect. $Interactions_i$ is the set of interaction terms between each variable in the regression and the nuclear accident day (i.e. $Small\_Close_i * E_{t,0}$, $Big\_Far_i * E_{t,0}$ and $Small\_Far_i * E_{t,0}$). $Controls_i$ is the set of control variables where: $r_{i,t-j}$ is the lagged dependent variable—the jth previous day rate of return, $WD_{k,t}$ with $k = 1, \ldots, 4$ are dummy variables for the day of the week (Monday, Tuesday, Wednesday, and Thursday), and Tax_t is a dummy variable for the first five days of the taxation year. The second model I run is the following:

$$r_{i,t} = \gamma_0 + \gamma_1 E_{t,0} + \gamma_2 Size_i + \gamma_3 Close_i + \gamma_4 Nuclear_i + \gamma_5 Clean_i + \gamma_6 interactions_i + \gamma_7 controls_i + \epsilon_t, \tag{4}$$

where $r_{i,t}$ is the rate of return of stock i on day t for all U.S. companies, γ_0 is the regression intercept, $E_{t,0}$, stands for possible event effect, and $Size_i$ is a dummy variable indicating the size of the stocks and it is equal to 1 if stock i is large (i.e. belongs to deciles 1-5) and 0 if is small (i.e. belongs to deciles 6-10). Furthermore, $Close_i$ is a dummy variable equal to 1 if stock i is in the same state in which the nuclear accident occurs, $Nuclear_i$ is a dummy variable equal to 1 if stock i belongs to the nuclear energy industry, and $Clean_i$ is a dummy variable equal to 1 if stock i belongs to the clean energy industry. $Interactions_i$ is the set of interaction terms between each variable in the regression and the nuclear accident day. $Controls_i$ is the set of control variables for presence of serial correlation, “Monday” effect, and “turn-of-the-year” effect. Like before, both regression’s standard errors are clustered by firm (using their CUSIP - Committee on Uniform Securities Identification Procedures code).

I test the following hypotheses. First, I test whether the geographic proximity of information has a statistically significant impact on the financial markets. I observe the stock returns of the U.S. publicly listed companies as a result to the nuclear events that took place in the U.S., France, and Japan. I predict that the event effect will be strongest for the companies having exposure to the U.S. events since these companies are geographically closer to both the place of the accident and to the financial markets (Ichev and Marinč, 2017; Engelberg and Parsons, 2011).

Second, I observe whether the event effect is stronger for small companies’ returns relative to large companies. Past research suggests that local investors are usually the ones investing in small firms, hence their sentiment is affected by event information that is specific to the place and firm that they invest into (see, Brown and Cliff, 2005; Edmans et al., 2007).

Third, a nuclear accident raises the general awareness of the possible risks of using nuclear energy. When a nuclear accident happens supervisory authorities usually overhaul existing safety procedures, which may lead to costly refurbishments in nuclear power plants, laboratories and testing premises. Hence, I anticipate companies from the nuclear energy industry to be negatively affected by the event of a nuclear accident. In addition, policymakers may launch programs to expedite the transition to non-nuclear, alternative energies where I would expect the companies in the non-nuclear, alternative energy sector to be positively affected. Having this in mind, I further select the 11 largest industries, by contribution to the U.S. GDP, and test how (positively or negatively) the nuclear accident events affect each industry.

Fourth, nuclear accidents by nature are expected to increase investor anxiety - which in turn affects investor sentiment and company returns. Motivated by Baker and Wurgler (2007), I proxy investor sentiment through the implied volatility and I observe whether the nuclear accident events affect the implied volatility on the day of the accident.

Fifth, disastrous events such as nuclear accidents are expected to trigger fear among investors (Donadelli et al., 2016b). Hence, I hypothesize that the influence of the accidents channels through the fear channel and triggers fear and bad mood among the investors, which contributes to depressed stock prices.

3.6 Results

3.6.1 Event Study

In this subsection I present the results of the event-study methodology. Table 3.1 depicts the CARs around the nuclear accident events from the one-factor market model. Panel 1 of Table 3.1 shows that the one-factor market model CARs on the event day are statistically significant and negative up to ten days after the accident - for the U.S. companies observed upon the nuclear accidents taking place on U.S. soil. For example, the [-5, 5], [0, 5], [0, 10], and [0, 20] event windows yield negative CARs with statistical significance varying between at 10% and 1% significance level and Patell z-scores of -3.101, -1.645, -2.812, and -1.203 respectively.

In Panel 2 and Panel 3 of Table 3.1, I categorize the nuclear accident events on whether they took place in Japan and in France. For the nuclear accidents that took place in Japan, I observe generally positive CARs for all event windows, but statistically significant at 10% only for the [-5, +5] event window. For the nuclear accident events that took place in France I observe similar results pattern. The CARs are positive for all event windows and statistically significant at 1% significance level. From the first three panels, one can draw a conclusion that nuclear accidents taking place in the same location as companies' founding location negatively and statistically significantly affect companies CARs. The effects that I observe from the nuclear accidents occurring far away from the birthplace of the companies are either statistically insignificant or having an opposite sign.

Panel 4 of Table 3.1 presents CARs results for the sub-sample of U.S. companies operating in the nuclear energy sector. I observe the nuclear energy sector companies upon the nuclear accidents that take place on U.S. soil. Consistent with Panel 1 of Table 1, the CARs are negative and statistically significant for all event windows where the [0, +10] window shows the strongest effect (-0.475% with Patell z-score of -2.808). This result is in line with Aktar

(2005) who provides a potential reason for this particular effect. Aktar (2005) concludes that an event of such nature, such that of a nuclear accident, is usually reflected in firms' stock returns only after ten days or more from the event day, since the actual reason for the occurrence of the accident is kept unclear, intentionally or not, from the greater public to prevent panic and over-reaction, as well as to ensure the security of the country.

Panel 5 and Panel 6 of Table 3.1 present CARs results for the same sub-sample as in Panel 1 of Table 3.1, but for the nuclear accidents taking place in Japan and France. The CARs are generally negative and statistically significant for all event windows apart from the [-5, +5] and [0, +20] when encountering events taking place in France. It is important to note that the number of observations in these two panels significantly drops due to the lower number of events in Japan and France than in the U.S. in the period from 1944 to 2017.

Panel 7, Panel 8 and Panel 9 of Table 3.1 show the CARs results for the sub-sample of U.S. companies operating in the clean energy sector. Like before, I observe the nuclear accident events taking place in the U.S., Japan, and France. Interestingly, the CARs are generally positive and statistically significant on at least 10% significance level. There are two potential reasons for this result which goes along with Ferstl et al. (2012). First, it might be that once a nuclear accident occurs, investors shift their investments and future investment intentions towards the clean energy sector. Second, in case of a nuclear energy accident, government authorities put in force radical changes – even shutting down - to the nuclear energy sector, hence the clean energy sector firms benefit from more attention and investment inflows.

Overall, the event study analysis points to an existing impact of the nuclear accident events on the U.S. companies' stock returns. I stress that the event study results are weaker than the regression results reported in the next section due to the fact that I employ the non-overlapping selection criteria of the events which lowers the total number of observations available.

Table 3.1 Event Study - cumulative average abnormal return results

The table depicts the cumulative average abnormal returns (CARs) around the event day (t=0) for stocks with exposure to the nuclear accidents in the period from 1944 to 2017. The abnormal return on day t is calculated as the difference between the observed rate of return and the ex-post expected rate of return on day t. The one-factor market model $\boldsymbol{r_{i,t} = \alpha_0 + \beta_1 r_{m,t} + \varepsilon_t}$, where $\boldsymbol{r_{i,t}}$ is the return on stock $\boldsymbol{i}$ in period t and $\boldsymbol{r_{m,t}}$ is the S&P 500 return, is estimated using a 250-day estimation window over four event windows: [-5, +5], [0, +5], [0, +10] and [0, +20]. The second column reports the number of observations, the third column is each CAR value (in %) and fourth column reports the Patell z-score where one, two, and three asterisks indicate a significance level of 10%, 5%, and 1%, respectively. Panel 1 to Panel 9 categorize the events and companies by location and industry type. The event selection procedure follows the *last/first* occurrence criteria which guarantees non-overlapping event windows during the period of observation.

Event Window	No. of observations	CAR (%)	Patell z-score
Panel 1. All U.S. Companies vs. U.S. Events			
[-5, +5]	14860	-0.157	-3.101***
[0, +5]	14860	-0.058	-1.645*
[0, +10]	14860	-0.182	-2.812***
[0, +20]	14860	-0.135	-1.203
Panel 2. All U.S. Companies vs. Japan Events			
[-5, +5]	1368	0.150	1.646*
[0, +5]	1368	0.112	0.993
[0, +10]	1368	-0.040	-0.895

[0, +20]	1368	0.401	0.993
Panel 3. All U.S. Companies vs. France Events			
[-5, +5]	1197	0.686	5.287***
[0, +5]	1197	0.464	3.574***
[0, +10]	1197	0.876	7.111***
[0, +20]	1197	1.081	7.022***
Panel 4. U.S. Nuclear Energy Companies vs. U.S. Events			
[-5, +5]	908	-0.232	-1.930*
[0, +5]	908	-0.372	-3.522***
[0, +10]	908	-0.475	-2.808***
[0, +20]	908	-0.420	-1.800*
Panel 5. U.S. Nuclear Energy Companies vs. Japan Events			
[-5, +5]	147	1.211	1.144
[0, +5]	147	-0.580	-3.236***
[0, +10]	147	-1.389	-5.196***
[0, +20]	147	-0.303	-3.449***
Panel 6. U.S. Nuclear Energy Companies vs. France Events			
[-5, +5]	117	-0.372	-0.824
[0, +5]	117	-1.326	-4.146***
[0, +10]	117	-1.115	-2.131**
[0, +20]	117	-0.187	-0.620
Panel 7. U.S. Clean Energy Companies vs. U.S. Events			
[-5, +5]	118	0.881	0.693
[0, +5]	118	0.197	1.967**
[0, +10]	118	0.848	1.663*
[0, +20]	118	0.685	0.655
Panel 8. U.S. Clean Energy Companies vs. Japan Events			
[-5, +5]	36	-2.571	-0.745
[0, +5]	36	-0.599	-0.216
[0, +10]	36	0.155	1.072
[0, +20]	36	0.628	1.033
Panel 9. U.S. Clean Energy Companies vs. France Events			
[-5, +5]	27	3.586	1.752*
[0, +5]	27	3.233	1.981**
[0, +10]	27	6.136	1.665*
[0, +20]	27	8.072	1.140

3.6.2 Geographic Proximity of Information and Financial Markets

Motivated by Betzer et al. (2011) and Engelberg and Parsons (2011) I test whether the geographic proximity of information affects the U.S. financial markets. I observe the stock returns of the U.S. publicly listed companies as an aftermath to the nuclear events that take place in the U.S., France, and Japan. Table 3.2 summarizes the results of the regression analysis in (2). Panel A of Table 3.2 summarizes the results of the regression analysis in (2) including the control variables. Panel B of Table 3.2 presents the results of the regression without control variables. Standard errors are clustered by firm (using their CUSIP - Committee on Uniform Securities Identification Procedures code).

Panel A of Table 3.2 reveals that the daily rate of return coefficient of the U.S. companies is negative and statistically significant, as expected, to the nuclear accident events taking place on the U.S. soil ($E_{t,0}$; -0.296 with t-statistics of -10.51). Interestingly, the rate of return coefficient of the companies when exercised upon the events taking place in Japan is positive and statistically significant at 10% significance level. The regression coefficient for the companies when exercised upon the events taking place in France is positive too but of slightly higher magnitude than for the events from Japan, and also statistically significant on at least 10% significance level.

The results regarding the control variables i.e., serial correlation ($\sum_{j=1}^{3} r_{i,t-j}$), "Monday effects" ($\sum_{k=1}^{4} WD_{k,t}$), and "turn-of-the-year effect" (Tax_t) are similar to previous studies (see for ex. Kaplanski and Levy, 2010a and 2010b). The coefficients from lag 1 to lag 3, attributed to infrequent trading, happen to be both negative and positive and of smaller magnitude in general compared to the coefficients on the event day. Similarly, the "Monday effects" coefficients are negative and the "turn-of-the-year effect" coefficients are positive and statistically significant for the nuclear accidents taking place in the U.S. and France, but negative for the nuclear accidents in Japan.

To observe possible reversal pattern of the returns I look at the first four days ($\sum_{l=1}^{4} E_{l,t}$) after the event day. From Panel A of Table 3.2 I can observe that the rate of returns from the first four days following the event day vary in sign (negative/positive), they are weaker - which is an indicator for a reversal behavior, and significant (see, Panel A of Table 3.2, coefficients of $E_{t,1}$, $E_{t,3}$ and $E_{t,4}$) for all nuclear accident regions. On the second day following the event day, $E_{t,2}$, I record statistically insignificant coefficients for both Japanese and French nuclear accidents. My results do not rule out the existence of an effect for the nuclear accidents in Japan and France on that day, but rather suggest that I could not observe it. This may be due to the smaller number of nuclear accident events in these two locations, proliferation within the media, and greater variation in the period.

Lastly, in Panel B of Table 3.2 I check the robustness of my results by running the regression analysis in (2) excluding the control variables. Similar to Panel A of Table 3.2, the rate of return coefficient of the U.S. companies is negative and statistically significant to the nuclear accident events taking place on U.S. soil, positive upon the events taking place in Japan and also positive for the companies when exercised upon the events taking place in France.

To sum up, Table 3.2 reveals that the nuclear accidents event effect is present for all event locations. The stocks of the companies exposed to the events located in the U.S. exhibit a pronounced negative behavior, potentially as a result of the geographic proximity of the information to the financial markets. Furthermore, the table shows a reversal pattern on the first day after the event day accompanied by negative/positive and statistically significant "Monday effects," "turn-of-the-year effect," and two-day significant serial correlation. This result provides support for my first hypothesis that the geographic proximity matters for the companies that are geographically closer to both the nuclear accident location as well as to the financial markets.

Table 3.2 Geographic proximity effect on financial markets

The table reports the results of the following regression:

$$r_{i,t} = \gamma_0 + \sum_{j=1}^{3} \gamma_{1,i} r_{i,t-j} + \sum_{k=1}^{4} \gamma_{2,k} WD_{k,t} + \gamma_3 Tax_t + \sum_{l=0}^{4} \gamma_{4,l} E_{l,t} + \epsilon_t,$$

where $\boldsymbol{r_{i,t}}$ is the rate of return of stock *i* on day *t* with exposure of its operations towards the U.S., $\boldsymbol{\gamma_0}$ is the regression intercept, $\boldsymbol{r_{i,t-j}}$ is the lagged dependent variable—the *j*th previous day rate of return, $\boldsymbol{WD_{k,t}}$ with $\boldsymbol{k = 1, \ldots, 4}$ are dummy variables for the day of the week (Monday, Tuesday, Wednesday, and Thursday), $\boldsymbol{Tax_t}$ is a dummy variable for the first five days of the taxation year, and $\boldsymbol{E_{l,t}}$ with $\boldsymbol{l = 0 \ldots 4}$, stands for possible event effect and reversal effect indicator. The events occurred in the period from 1944 to 2017 and include a total number of 102 events on three locations: U.S., Japan and France. From the total number of events, 87 took place in the U.S., 7 in France, and 8 in Japan. The first line reports the regression coefficients, while the second line reports the corresponding t-values (in brackets). One, two, and three asterisks indicate a significance level of 10%, 5%, and 1%, respectively.

	γ_0	R_{t-3}	R_{t-2}	R_{t-1}	Mon.	Tue.	Wed.	Thu.	Tax	$E_{t,0}$	$E_{t,1}$	$E_{t,2}$	$E_{t,3}$	$E_{t,4}$	R^2	Obs.
PANEL A: Regression results including the control variables																
U.S. Com. – U.S. Events	-0.116***	-0.022	-0.002	0.004	-0.167***	-0.063***	-0.030***	-0.061***	0.112***	-0.296***	-0.127***	0.019*	-0.066***	0.019***	0.100	348818
	(-46.47)	(-0.48)	(-0.03)	(0.06)	(-23.56)	(-11.03)	(-18.18)	(-29.36)	(5.85)	(-10.51)	(-3.37)	(1.69)	(-12.31)	(3.72)		
U.S. Com. – Jap. Events	-0.084***	-0.010	0.275***	0.041***	-0.006	0.039***	0.011***	-0.050***	-0.108***	0.044*	0.026*	-0.514	-0.003	-0.157**	0.201	32073
	(-31.91)	(-0.70)	(15.20)	(5.71)	(-0.91)	(7.74)	(4.07)	(-11.93)	(-9.29)	(1.68)	(1.66)	(-1.51)	(-0.08)	(-2.24)		
U.S. Com. – Fra. Events	0.068***	0.236***	0.010	0.270***	-0.219***	0.014**	0.032***	-0.010*	0.031***	0.053**	0.095***	0.018	0.556***	0.307***	0.190	28063
	(10.89)	(8.80)	(0.45)	(8.05)	(-26.75)	(2.08)	(5.21)	(-1.71)	(9.26)	(1.97)	(11.91)	(0.63)	(26.32)	(10.42)		
PANEL B: Regression results without the control variables																
U.S. Com. – U.S. Events	-0.053***									-0.247***	-1.021***	0.031**	-0.082***	0.014***	0.090	348818
	(-53.21)									(-11.18)	(-2.75)	(2.07)	(-14.81)	(2.99)		
U.S. Com. – Jap. Events	0.081***									0.039*	0.040*	-0.479	-0.016	-0.166**	0.010	32073
	(39.41)									(1.65)	(1.75)	(-1.64)	(-0.51)	(-2.09)		
U.S. Com. – Fra. Events	0.037***									0.098*	0.026***	0.040	0.479***	0.302***	0.080	28063
	(10.83)									(1.74)	(15.98)	(0.92)	(19.67)	(9.68)		

3.6.3 U.S. Nuclear Accidents Effect and Firm Size

Inspired by Brown and Cliff (2005) and Edmans et al. (2007), I test whether the U.S. nuclear accident events effect is stronger for the stocks of small companies relative to the stocks of large companies. Table 3.3 presents the regression results, where both the event location as well as the companies are from the U.S. Dependent variable is the rate of return on a portfolio comprised of stocks belonging to a firm-size decile. Deciles rank from 1 to 10, where decile 1 is composed of the largest firms by size and decile 10 is composed of the smallest firms by size.

Similar to previous studies (e.g., Schwert, 1990b), on the day of the event, $E_{t,0}$, the event effect coefficients tend to increase as size decreases. The regression coefficient for the firms in decile 1 is -0.154 with t-statistics of -2.38. The regression coefficients for the firms in decile 10 is -0.252 with t-statistics of -3.72.

Regarding the control variables, the serial correlation coefficients for 1 and 2 lags are positive and lag 3 coefficient is negative, corresponding to the largest stocks, but statistically insignificant. In addition, statistically significant “Monday effect” as well as “turn-of-the-year effect” are recorded throughout all 10 size deciles.

Lastly, to observe a possible reversal pattern of stock returns I look at the four days following the event day. On the first, third and fourth day following the event day, I observe positive coefficients for all size deciles, however statistically insignificant. On the second day following the event day, the coefficients are negative and insignificant too.

To sum up, Table 3.3 reports that the event effect is more pronounced for small stocks rather than for large stocks on the event day. One potential explanation could posit that the information dissemination of small stocks is poorer than the information dissemination of large stocks. Fang and Peress (2009) conclude that it may be due to the disparity between the small and large stocks, media can especially influence small stocks, for which the information dissemination is limited. For large stocks, information dissemination channels are already well-established, thus the potential impact is more restrained. Furthermore, the observation of a possible reversal pattern of companies’ stock returns do not rule out the existence of an effect for the nuclear accidents, but rather suggest that I could not observe it.

Table 3.3 Stocks classified by size

The table reports the results of the following regression:

$$r_{i,t} = \gamma_0 + \sum_{j=1}^{3} \gamma_{1,i} r_{i,t-j} + \sum_{k=1}^{4} \gamma_{2,k} WD_{k,t} + \gamma_3 Tax_t + \sum_{l=0}^{4} \gamma_{4,l} E_{l,t} + \epsilon_t \,,$$

where $r_{i,t}$ is the rate of return of stock *i* on day *t* classified by size, γ_0 is the regression intercept, $r_{i,t-j}$ is the lagged dependent variable—the *j*th previous day rate of return, $WD_{k,t}$ with $k = 1, \dots, 4$ are dummy variables for the day of the week (Monday, Tuesday, Wednesday, and Thursday), Tax_t is a dummy variable for the first five days of the taxation year, and $E_{l,t}$ with $l = 0 \dots 4$, stands for possible event effect and reversal effect indicator. The events occurred in the period from 1944 to 2017 in the U.S. and include a total number of 87 events. Decile 1 represents the largest firms whereas Decile 10 represents the smallest firms. The first line reports the regression coefficients, while the second line reports the corresponding t-values (in brackets). One, two, and three asterisks indicate a significance level of 10%, 5%, and 1%, respectively.

Size Decile	γ_0	R_{t-3}	R_{t-2}	R_{t-1}	Mon.	Tue.	Wed.	Thu.	Tax	$E_{t,0}$	$E_{t,1}$	$E_{t,2}$	$E_{t,3}$	$E_{t,4}$	R^2	Obs.
Decile 1 (largest firms)	-0.227*** (-15.07)	0.023 (0.42)	-0.002 (-0.04)	0.037 (0.66)	-0.280*** (-12.27)	-0.266*** (-12.25)	-0.139*** (-6.37)	-0.119*** (-5.50)	0.665*** (12.85)	-0.154** (-2.38)	0.035 (0.62)	-0.005 (-0.07)	0.021 (0.38)	0.026 (0.46)	0.159	34878
Decile 2	-0.230*** (-16.28)	0.035 (0.76)	-0.030 (-0.53)	0.044 (0.83)	-0.309*** (-14.46)	-0.254*** (-12.36)	-0.145*** (-7.08)	-0.130*** (-6.46)	0.535*** (11.11)	-0.201*** (-3.26)	0.041 (0.77)	-0.033 (-0.58)	0.032 (0.69)	0.032 (0.62)	0.160	34878
Decile 3	-0.203*** (-13.99)	0.006 (0.11)	-0.006 (-0.10)	0.004 (0.07)	-0.297*** (-13.26)	-0.213*** (-10.06)	-0.109*** (-5.08)	-0.106*** (-5.06)	0.447*** (9.02)	-0.224*** (-3.34)	0.001 (0.02)	-0.009 (-0.15)	0.003 (0.06)	0.052 (0.93)	0.047	34878
Decile 4	-0.206*** (-13.28)	0.059 (0.96)	0.002 (0.02)	0.018 (0.27)	-0.288*** (-12.13)	-0.201*** (-8.73)	-0.120*** (-5.25)	-0.102*** (-4.54)	0.366*** (6.53)	-0.268*** (-3.73)	0.014 (0.21)	-0.003 (-0.04)	0.055 (0.89)	0.025 (0.41)	0.136	34878
Decile 5	-0.180*** (-11.33)	0.051 (0.80)	-0.048 (-0.70)	0.025 (0.36)	-0.268*** (-10.96)	-0.163*** (-6.91)	-0.085*** (-3.65)	-0.088*** (-3.82)	0.323*** (5.55)	-0.193*** (-4.08)	0.020 (0.29)	-0.052 (-0.78)	0.046 (0.72)	0.015 (0.25)	0.030	34878
Decile 6	-0.167*** (-10.54)	0.023 (0.37)	-0.056 (-0.80)	0.027 (0.39)	-0.259*** (-10.53)	-0.138*** (-5.80)	-0.064*** (-2.71)	-0.075*** (-3.21)	0.280*** (4.62)	-0.190*** (-3.86)	0.022 (0.31)	-0.061 (-0.87)	0.018 (0.29)	0.004 (0.06)	0.127	34878
Decile 7	-0.154*** (-9.64)	0.044 (0.69)	-0.029 (-0.42)	0.022 (0.32)	-0.239*** (-9.66)	-0.112*** (-4.67)	-0.058** (-2.44)	-0.062*** (-2.63)	0.230*** (3.79)	-0.207*** (-4.11)	0.017 (0.24)	-0.035 (-0.50)	0.039 (0.61)	-0.008 (-0.11)	0.123	34878
Decile 8	-0.153*** (-9.97)	0.041 (0.67)	-0.056 (-0.84)	0.013 (0.20)	-0.233*** (-9.83)	-0.107*** (-4.64)	-0.049** (-2.14)	-0.066*** (-2.94)	0.167*** (2.87)	-0.250*** (-3.50)	0.009 (0.13)	-0.060 (-0.90)	0.037 (0.60)	0.006 (0.09)	0.121	34878
Decile 9	-0.144*** (-9.76)	0.041 (0.25)	-0.061 (-0.94)	0.015 (0.70)	-0.218*** (-9.52)	-0.088*** (-3.98)	-0.041* (-1.85)	-0.055** (-2.52)	0.115** (2.07)	-0.269*** (-3.89)	0.011 (0.17)	-0.065 (-1.01)	0.037 (0.62)	0.012 (0.20)	0.120	34878
Decile 10 (smallest firms)	-0.109*** (-6.97)	-0.019 (-0.33)	-0.033 (-0.53)	0.015 (0.26)	-0.156*** (-6.58)	-0.047** (-2.02)	-0.020 (-0.88)	-0.058** (-2.55)	0.033 (0.58)	-0.252*** (-3.72)	0.011 (0.19)	-0.037 (-0.59)	-0.023 (-0.40)	0.022 (0.37)	0.111	34878

3.6.4 U.S. Nuclear Accidents and U.S. Industries

Table 3.4 presents the regression results where I classify the U.S. stocks by industry of operation. On the day of the event (for the nuclear accident events in the U.S.), all coefficients are large, negative, and statistically significant on at least 5% significance level, except for the clean energy industry[30]. The stock return coefficient of the clean energy industry is positively affected by the nuclear accidents.

The results from Table 3.4 confirm my expectations, showing evidence for the industry effect. A possible reason for this effect is that investors anticipate an increase in cash flows to the clean energy industry due to, for example, government decisions and policy changes in favor of the clean energy industry, restrictions and tightening on the usage of nuclear energy, investing in R&D, etc. The result is related to Ferstl et al. (2012) and Hirshleifer et al. (2013) who find that innovative efficiency and citations scaled by R&D expenditures positively determine future stock returns. A conclusion would be that the investor sentiment about the performance of certain industries may be an important element that drives investment decisions, and thus company returns Lucey and Dowling (2005).

3.6.5 U.S. Nuclear Accidents and Implied Volatility

Baker and Wurgler (2007) use securities' implied volatility as a proxy for investor sentiment. Following their research strategy, I test whether the U.S. nuclear accident events affect the implied volatility of the U.S. publicly listed companies. I employ two measures of the fear index,[31] the VIX and VXO indices that serve as a proxy for investor sentiment (see Whaley, 2000).

Figure 3.2 reveals the volatility pattern around the nuclear accident event days. Figure 3.2 reveals an upward shift of the volatility indices on the day of the event (at t=0) and a mild persistence of the effect on the first day following the event day. I employ a matched-pair t-test to test the significance of the effect. I observe statistically significant volatility surge on the nuclear accident days, with t-values of $t=7.64$ ($P<0.001$) and $t=7.57$ ($P<0.008$) for VIX and VXO respectively.

[30] Clean energy industry is classified into: solar energy, hydropower, wind energy, fuel cell technology, geothermal electric power plants, and biodiesel (www.icis.com).

[31] Chicago Board of Options Exchange (CBOE) launched the "Fear Index" in 1993. VIX relies on the average price of the options of the S&P500 Index, whereas VXO is constructed according to the Black-Scholes (1973) and relies on the average implied volatility of the options on the S&P100 Index as measured by the model.

Table 3.4 Event effect on U.S. Industries

The table reports the results of the following regression:

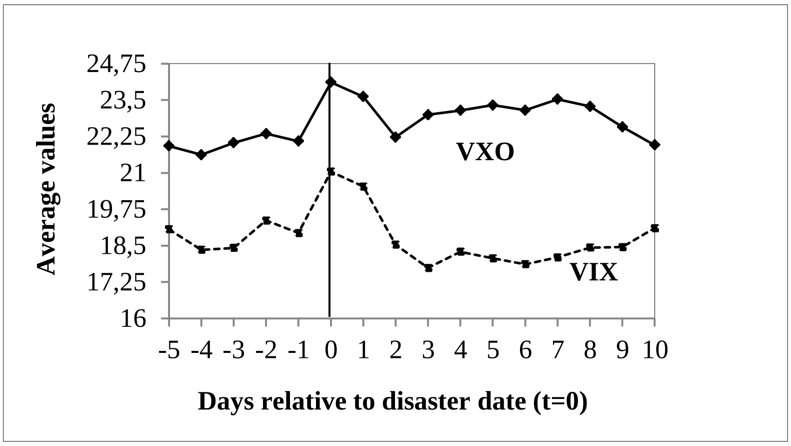
$$r_{i,t} = \gamma_0 + \sum_{j=1}^{3}\gamma_{1,i} r_{i,t-j} + \sum_{k=1}^{4}\gamma_{2,k} WD_{k,t} + \gamma_3 Tax_t + \sum_{l=0}^{4}\gamma_{4,l} E_{l,t} + \epsilon_t,$$

where $\boldsymbol{r_{i,t}}$ is the rate of return of stock i on day t classified by industry of operation, $\boldsymbol{\gamma_0}$ is the regression intercept, $\boldsymbol{r_{i,t-j}}$ is the lagged dependent variable—the jth previous day rate of return, $\boldsymbol{WD_{k,t}}$ with $\boldsymbol{k = 1, \ldots, 4}$ are dummy variables for the day of the week (Monday, Tuesday, Wednesday, and Thursday), $\boldsymbol{Tax_t}$ is a dummy variable for the first five days of the taxation year, and $\boldsymbol{E_{l,t}}$ with $\boldsymbol{l = 0 \ldots 4}$, stands for possible event effect and reversal effect indicator. The events occurred in the period from 1944 to 2017 in the U.S. and include a total number of 87 events. The industries have been selected by their contribution to the U.S. GDP. Below presented, are the 11 largest by contribution industries according to S&P Dow Jones Industry Indexes. The first line reports the regression coefficients, while the second line reports the corresponding t-values (in brackets). One, two, and three asterisks indicate a significance level of 10%, 5%, and 1%, respectively.

Industry name	γ_0	R_{t-3}	R_{t-2}	R_{t-1}	Mon.	Tue.	Wed.	Thu.	Tax	$E_{t,0}$	$E_{t,1}$	$E_{t,2}$	$E_{t,3}$	$E_{t,4}$	R^2	Obs.
Medical Equipment	-0.114***	-0.038	-0.057	0.136	-0.159***	-0.054	0.012	-0.042	0.125	-0.425***	0.129	-0.064	-0.045	0.026	0.191	6299
	(-4.54)	(-0.48)	(-0.67)	(1.59)	(-4.37)	(-1.53)	(0.34)	(-1.19)	(1.39)	(-4.34)	(1.51)	(-0.75)	(-0.57)	(0.29)		
Chemicals	-0.130***	0.065	-0.050	0.016	-0.199***	-0.064**	-0.027	-0.065**	0.077	-0.277***	0.010	-0.056	0.060	-0.026	0.110	6299
	(-6.73)	(0.96)	(-0.62)	(0.21)	(-6.97)	(-2.23)	(-0.97)	(-2.35)	(1.13)	(-3.48)	(0.14)	(-0.68)	(0.88)	(-0.38)		
Nuclear Energy	-0.137***	-0.118	-0.050	0.052	-0.282***	-0.067*	-0.026	-0.021	0.305***	-0.329***	-0.046	-0.056	-0.113	-0.017	0.140	6299
	(-5.04)	(-1.11)	(-0.48)	(0.52)	(-7.05)	(-1.70)	(-0.66)	(-0.55)	(3.10)	(-3.08)	(-0.46)	(-0.53)	(-1.06)	(-0.17)		
Steel	-0.118***	0.016*	0.018	0.029	-0.231***	-0.014	-0.011	-0.093***	0.278***	-0.435***	0.020	0.096	0.159	-0.071	0.141	6299
	(-4.79)	(1.69)	(0.16)	(0.31)	(-6.31)	(-0.41)	(-0.31)	(-2.62)	(3.11)	(-4.02)	(0.22)	(0.09)	(1.60)	(-0.72)		
Electrical Equipment	-0.135***	0.124	-0.069	0.070	-0.197***	-0.082**	-0.029	-0.077**	0.052	-0.350***	0.004	-0.075	0.118	-0.019	0.199	6299
	(-5.76)	(1.34)	(-0.74)	(0.08)	(-5.67)	(-2.36)	(-0.85)	(-2.29)	(0.60)	(-3.60)	(0.01)	(-0.81)	(1.27)	(-0.23)		
Mining	-0.132***	0.022	-0.107	-0.056	-0.226***	-0.098**	-0.060	-0.074**	0.166*	-0.261**	-0.061	-0.011	0.017	-0.019	0.181	6299
	(-5.06)	(0.23)	(-0.98)	(-0.55)	(-5.88)	(-2.57)	(-1.60)	(-1.97)	(1.81)	(-2.34)	(-0.59)	(-1.03)	(0.18)	(-0.19)		
Coal	-0.121***	0.075	0.041	0.014	-0.251***	-0.094**	-0.051	-0.037	0.092	-0.333**	0.045	0.032	0.065	-0.208*	0.170	6299
	(-3.64)	(0.62)	(0.28)	(0.12)	(-5.21)	(-1.99)	(-1.08)	(-0.80)	(0.84)	(-2.23)	(0.04)	(0.22)	(0.54)	(-1.65)		
Crude Oil	-0.139***	0.029	0.072	0.049	-0.211***	-0.068**	-0.062**	-0.094***	-0.0862	-0.339***	0.043	0.019	0.023	0.032	0.101	6299
	(-6.39)	(0.37)	(0.08)	(0.61)	(-6.54)	(-2.17)	(-1.98)	(-3.01)	(-0.12)	(-3.97)	(0.55)	(0.02)	(0.30)	(0.40)		
Utilities	-0.103***	0.073	-0.057	-0.010	-0.109***	-0.049***	-0.053***	-0.051***	0.062	-0.153***	-0.013	-0.059	0.072	0.018	0.100	6299
	(-9.32)	(1.57)	(-1.22)	(-0.23)	(-6.48)	(-3.03)	(-3.26)	(-3.12)	(1.46)	(-3.14)	(-0.28)	(-1.27)	(1.52)	(0.41)		
Insurance	-0.115***	-0.035	-0.127	0.065	-0.139***	-0.046	-0.032	-0.037	0.056	-0.316***	0.059	-0.132	-0.041	-0.010	0.167	6299
	(-5.08)	(-0.42)	(-1.54)	(0.82)	(-4.22)	(-1.43)	(-1.01)	(-1.16)	(0.72)	(-3.32)	(0.75)	(-1.61)	(-0.48)	(-0.13)		
Clean Energy	0.136***	0.041	-0.029	-0.027	0.203***	0.101***	-0.057*	-0.065*	0.226***	0.338**	0.032	0.035	0.036	0.051	0.192	6299
	(5.60)	(0.50)	(-0.34)	(-0.34)	(5.72)	(2.89)	(-1.66)	(-1.89)	(2.83)	(2.31)	(0.40)	(0.40)	(0.44)	(0.65)		

One potential explanation for the result may indicate that the surge in the implied volatility on the event day is due to a fear or anxiety effect induced by the nuclear accident events. Another reason for the rapid increase in the volatility may be due to an increase in the actual market volatility that coincidentally occurs at the same time as nuclear accidents. In his research, Schwert (2003) observes a long-time period of market volatility and concludes that the overall volatility of the market is higher during economic recessions and banking crisis. In this particular case, it does not mean that there exactly was an overlapping event going on, but that other reasons for the market volatility surge around the event day may exist. For example, the nuclear accidents effect may be related to some confounding variables (e.g., financial markets crashes, economic crises).

Figure 3.2 Fear Index Around Event Days



Notes. The figure depicts the average value of VIX and VXO indices around the event day (t=0). The indices cover the period of all publicly known nuclear accident events that took place in the U.S., which total number is 87.

3.6.6 The Fear Channel: Event Effect Across the U.S. States

Motivated by Donadelli et al. (2016b), I observe whether the stock prices around the nuclear accident event days come as an aftermath of the accidents triggering fear and bad mood among the investors. Table 3.5 summarizes the results of the regression analysis in (3). Standard errors are clustered by firm (using their CUSIP - Committee on Uniform Securities Identification Procedures code). Model (1), model (2), and model (3) present the results for all U.S. firms exposed to the events taking place on the U.S. soil. On the nuclear accident days, the regression coefficients (associated with $E_{t,0}$) in all three models are negative and highly statistically significant. Model (2) that estimates the regression analysis in (3) without the control variables shows that small companies which are in the same U.S. state as the nuclear accidents are negatively influenced by the accidents upon their stock returns (coefficient on $Small\_Close_i * E_{t,0}$, -1.507 with t-value of -2.01). I also observe negative coefficient, see -1.501 with t-value of -1.99, for the small size firms which are located far from the nuclear accidents (i.e., outside the state where the event happens). In addition, looking at model (3) of Table 3.5, I find the same sign of the coefficients as in model (2) to which I further observe negative and statistically significant “Monday effects”, and positive and significant “turn-of-the-year effect”.

Model (4), model (5), and model (6) present the results for the nuclear energy industry firms exposed to the events taking place on U.S. soil. Like the first three models, on the nuclear accident days (i.e. $E_{t,0}$) the coefficients in the models are negative and statistically significant. I observe negative coefficients for the small companies located in the same U.S. state as the nuclear accidents too. For example, in model (6) one can observe the coefficient on $Small\_Close_i * E_{t,0}$, which is negative 4.232 and statistically significant at 10% significance level. In addition, I observe negative coefficient for the small size firms which are located far from the nuclear accidents. The control variables considered are statistically insignificant except for the “turn-of-the-year effect”.

These results rather suggest that the small firms which are located outside of the state where the nuclear accident occurred, were affected almost as much, in magnitude, as the firms located in the state where the nuclear disaster occurred. A potential explanation for such results goes along with Donadelli et al. (2016b) and Kaplanski and Levy (2010a) who point to the fear, anxiety, and especially bad mood as highly manifested decision-driver among the financial markets’ investors moments after a dramatic accident happens.

Lastly, model (7), model (8), and model (9) present the results for the clean energy industry firms exposed to the events taking place on U.S. soil. Consistent with my previous results, the clean energy industry firms appear to benefit from the nuclear accidents, however I record no statistically significant results for the control variables.

3.6.7 The Fear Channel: Event Effect on all U.S. Companies

In this sub-section I expand the analysis from sub-section 3.6.6. Table 3.6 presents the results of the regression analysis in (4). Standard errors are clustered by firm (using their CUSIP - Committee on Uniform Securities Identification Procedures code). Model (1) to model (10) observe all U.S. companies exposed to the nuclear accident events taking place on the U.S. soil. On the nuclear accident days (i.e. $E_{t,0}$), I record negative and statistically significant coefficients in all models apart from model (7) and model (8), which lack the sufficient statistical significance. In line with the results in sub-section 3.6.3, I find some evidence that company size is yet again having role in absorbing the event effect.

Regarding company distance to the nuclear accidents, the results in Table 3.6 are consistent with previous findings, suggesting that the companies which are located in the same U.S. state where the nuclear accidents occur are negatively and statistically significantly affected by the event itself (for example, in model (3) and model (4) $Close_i * E_{t,0}$ coefficients are -0.370 with t-value of -1.98 and -0.400 with t-value of -1.84, respectively).

Table 3.5 The Fear Channel: Event effect across U.S. states

The table reports the results of the following regression:

$r_{i,t} = \gamma_0 + \gamma_1 Small\_Close_i + \gamma_2 Big\_Far_i + \gamma_3 Small\_Far_i + \gamma_4 E_{t,0} + \gamma_5 interactions_i + \gamma_6 controls_i + \epsilon_t,$

where $r_{i,t}$ is the rate of return of stock i on day t for all U.S. firms, U.S. Nuclear Energy firms and U.S. Clean Energy firms respectively, γ_0 is the regression intercept, $Small\_Close_i$ is a dummy variable equal to 1 if stock i is small (i.e. belongs to decile 6 to 10) and it is in the same state in which the nuclear accident occurs, and zero otherwise. Big_Far_i is a dummy variable equal to 1 if stock i is large (i.e. belongs to decile 1 to decile 5) and it is not in the same state in which the nuclear accident occurs, $Small\_Far_i$ is a dummy variable equal to 1 if stock i is small and it is not in the same state in which the nuclear accident occurs, and $E_{t,0}$, stands for possible event effect. $Interactions_i$ is the set of interaction terms between each variable in the regression and the nuclear accident day. $Controls_i$ is the set of control variables for presence of serial correlation, "Monday" effect, and "turn-of-the-year" effect. The events occurred in the period from 1944 to 2017 and include a total number of 87 events taking place across the U.S. Models (1) - (3) present regression results for all U.S. firms, models (4) - (6) present results for U.S. nuclear energy firms, and models (7) - (9) present results for the U.S. clean energy firms. The first line reports the regression coefficients, while the second line reports the corresponding t-values (in brackets). One, two, and three asterisks indicate a significance level of 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
r_i	All firms' rates of return	All firms' rates of return	All firms' rates of return	Nuclear energy firms' rates of return	Nuclear energy firms' rates of return	Nuclear energy firms' rates of return	Clean energy firms' rates of return	Clean energy firms' rates of return	Clean energy firms' rates of return
γ_0	-0.052***	-0.053***	-0.116***	-0.031***	-0.030***	-0.015	0.050***	0.051***	0.056***
	(-13.46)	(-13.45)	(-17.93)	(-4.45)	(-4.44)	(-2.09)	(7.52)	(7.51)	(3.74)
Small_Close	0.831**	0.845*	0.958***	1.710**	1.536*	1.557*	1.937*	1.849	1.850
	(2.22)	(1.94)	(1.97)	(2.35)	(1.71)	(1.72)	(1.64)	(0.38)	(0.38)
Big_Far	0.635***	0.629***	0.639***	-1.047	-0.964	-0.990	-0.690	-0.617	(-0.633)
	(4.19)	(4.13)	(4.22)	(-1.01)	(-0.92)	(-0.95)	(-0.68)	(-0.61)	(-0.62)
Small_Far	-0.162*	-0.140	-0.128	-0.278	-0.378	-0.348	0.143*	0.317	0.319
	(-1.73)	(-1.06)	(-0.97)	(-1.32)	(-0.43)	(-0.40)	(1.76)	(0.36)	(0.37)
$E_{t,0}$	-0.047***	-0.047***	-0.033***	-0.025**	-0.021**	-0.020**	0.046*	0.044*	0.047*
	(-4.93)	(-4.98)	(-3.50)	(-2.36)	(-2.31)	(-2.28)	(1.70)	(1.67)	(1.72)
Small_Close*$E_{t,0}$		-1.507**	-0.429**		-5.149*	-4.232*		8.085**	8.367**
		(-2.01)	(-1.96)		(-1.71)	(-1.69)		(2.38)	(2.39)
Big_Far* $E_{t,0}$		-0.386	-0.416		-6.794	-6.518		-4.642	-4.733
		(-0.28)	(-1.41)		(-0.55)	(-0.53)		(-1.06)	(-1.07)
Small_Far*$E_{t,0}$		-1.501**	-1.484*		-7.594*	-7.641*		2.713*	2.872*
		(-1.99)	(-1.66)		(-1.70)	(-1.71)		(1.75)	(1.77)
R_{t-3}			-0.054***			0.050			0.102
			(-6.50)			(0.74)			(1.58)
R_{t-2}			0.021			-0.020			0.024
			(1.23)			(-0.29)			(0.36)
R_{t-1}			-0.022**			0.083			0.008
			(-2.44)			(1.22)			(0.12)
Monday			-0.167***			-0.018			-0.015
			(-44.68)			(-0.84)			(-0.73)
Tuesday			-0.062***			0.005			0.008
			(-20.93)			(0.25)			(0.43)
Wednesday			-0.029***			-0.016			-0.007
			(-9.78)			(-0.75)			(-0.40)
Thursday			-0.060***			0.017			-0.026
			(-20.73)			(0.79)			(-1.26)
Tax			0.112***			0.265**			0.197*
			(6.75)			(2.13)			(1.63)
Observations	348818	348818	348818	6299	6299	6299	6299	6299	6299
R-squared	0.108	0.112	0.117	0.122	0.125	0.128	0.103	0.131	0.114

Regarding the industry of operation, the results point to a negative nuclear accidents influence on the companies operating in the nuclear energy industry. For example, in model (5) and model (6) the regression coefficients associated with $Nuclear_i * E_{t,0}$ are -0.325 and -0.361 respectively and are statistically significant at the 5% significance level. In addition, I observe positive and statistically significant (at the 10% significance level) regression coefficients for the companies operating in the clean energy industry.

The control variables across the models follow similar pattern as in my previous analyses. I observe negative and statistically significant regression coefficients associated with the "Monday" effect for nine out of ten of the models, and lastly, the regression coefficients associated with the "turn-of-the-year" effect are positive and statistically significant in all models.

3.7 Concluding remarks

This chapter documents that nuclear accident events in the period from 1944 to 2017 have statistically significant impact on the U.S. publicly listed companies. Inspired by previous studies showing that extreme events (e.g., Fukushima Daiichi nuclear disaster, Chernobyl nuclear disaster, aviation disasters; see Betzer et al., 2011; Bowen et al., 1983; Kaplanski and Levy, 2010a and 2010b) may impose a sharp decline in the financial markets which is different from the direct economic loss, I look for an explanation in the realm of behavioral finance. Behavioral finance studies show that dramatic events such as a nuclear accident event can enhance fear and risk aversion among the investors and thus affect investor sentiment.

I confirm the hypothesis that the geographic proximity of the information to the financial markets increases the importance of the event (related to the 1944 – 2017 nuclear accidents) and its impact on companies' stock returns. I find that the event effect is large, statistically significant and negative for the U.S. companies when the nuclear accidents take place on U.S. soil, and I record a stock returns reversal pattern on the first day after the event day accompanied by statistically significant "Monday effects" and "turn-of-the-year effect".
Additional tests reveal that the impact of the nuclear accidents differ across firm size and across firms belonging to specific industries. In addition, the implied volatility soars on the nuclear accident days, which may imply that the accident itself also affects investors' perceived risk. Finally, I confirm existence of a fear channel through which the influence of the nuclear accidents triggers fear among the investors that contributes to depressed stock prices.

Table 3.6 The Fear Channel: Event effect on all U.S. companies

The table reports the results of the following regression:

$$r_{i,t} = \gamma_0 + \gamma_1 E_{t,0} + \gamma_2 Size_i + \gamma_3 Close_i + \gamma_4 Nuclear_i + \gamma_5 Clean_i + \gamma_6 interactions_i + \gamma_7 controls_i + \epsilon_t,$$

where $r_{i,t}$ is the rate of return of stock i on day t for all U.S. companies, γ_0 is the regression intercept, $E_{t,0}$, stands for possible event effect, $Size_i$ is a dummy variable equal to 1 if stock i is large (i.e. belongs to decile 1 to decile 5) and 0 if is small (i.e. belongs to decile 6 to decile 10), $Close_i$ is a dummy variable equal to 1 if stock i is in the same state in which the nuclear accident occurs, $Nuclear_i$ is a dummy variable equal to 1 if stock i belongs to the nuclear energy industry, and $Clean_i$ is a dummy variable equal to 1 if stock i belongs to the clean energy industry. $Interactions_i$ is the set of interaction terms between each variable in the regression and the nuclear accident day. $Controls_i$ is the set of control variables for presence of serial correlation, “Monday” effect, and “turn-of-the-year” effect. The events occurred in the period from 1944 to 2017 and include a total number of 87 events taking place across the U.S. The first line reports the regression coefficients, while the second line reports the corresponding t-values (in brackets). One, two, and three asterisks indicate a significance level of 10%, 5%, and 1%, respectively.

	All firms’ rates of return									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
γ_0	-0.051***	-0.115***	-0.053***	-0.116***	-0.126***	-0.134***	0.121***	0.136***	-0.137***	-0.137***
	(-15.03)	(-15.46)	(-15.29)	(-15.01)	(-3.64)	(-4.14)	(3.90)	(5.60)	(-4.25)	(-4.33)
$E_{t,0}$	-0.051***	-0.377***	-0.045***	-0.031**	-0.315***	-0.321***	0.088	0.093	-0.129***	-0.114***
	(-3.64)	(-2.62)	(-4.65)	(-3.20)	(-3.24)	(-3.13)	(1.40)	(1.51)	(-3.08)	(-3.10)
Size	0.030*	0.020*								
	(1.68)	(1.65)								
Size*$E_{t,0}$	0.170	0.182*								
	(1.62)	(1.69)								
Close			0.170**	0.280*						
			(1.98)	(1.94)						
Close*$E_{t,0}$			-0.370**	-0.400*						
			(-1.98)	(-1.84)						
Nuclear					0.014	0.016			0.021*	0.024*
					(1.62)	(1.58)			(1.65)	(1.66)
Nuclear* $E_{t,0}$					-0.325**	-0.361**			-0.310*	-0.318*
					(-1.98)	(-2.01)			(-1.81)	(-1.79)
Clean							0.129*	0.135*	0.114	0.059
							(1.88)	(1.72)	(1.05)	(0.96)
Clean*$E_{t,0}$							0.225*	0.241*	0.189	0.197
							(1.95)	(1.81)	(1.53)	(1.62)
R_{t-3}		-0.054***		-0.055***		-0.114		0.041		-0.118
		(-6.50)		(-6.50)		(-1.21)		(0.50)		(-1.11)
R_{t-2}		0.021**		0.022**		-0.034		-0.024		-0.050
		(2.24)		(2.24)		(-0.45)		(-0.35)		(-0.48)
R_{t-1}		-0.022**		-0.023**		0.043		-0.023		0.052
		(-2.44)		(-2.44)		(0.51)		(-0.36)		(0.52)
Monday		-0.167***		-0.167***		-0.244***		0.212***		-0.282***
		(-4.68)		(-4.67)		(-3.94)		(5.77)		(-7.05)
Tuesday		-0.062**		-0.063**		-0.059*		0.103***		-0.067*
		(-1.94)		(-1.93)		(-1.73)		(2.80)		(-1.70)
Wednesday		-0.028***		-0.029***		-0.032		-0.057*		-0.026
		(-9.79)		(-9.78)		(-0.24)		(-1.66)		(-0.66)
Thursday		-0.060*		-0.060*		-0.022		-0.065*		-0.021
		(-1.73)		(-1.73)		(-0.50)		(-1.89)		(-0.55)
Tax		0.111***		0.112***		0.321***		0.225***		0.305***
		(6.74)		(6.75)		(3.24)		(2.86)		(3.10)
Observations	348818	348818	348818	348818	348818	348818	348818	348818	348818	348818
R-squared	0.109	0.111	0.115	0.121	0.142	0.163	0.112	0.118	0.211	0.119

GENERAL DISCUSSION AND CONCLUSION

This chapter provides an overview of the main findings as well as it elaborates on the theoretical and empirical contributions of the dissertation. The primary goal of this doctoral dissertation is to observe, examine, and evaluate the relationship between information dissemination in financial markets and particularly the impact on companies' stock returns. The rest of this chapter is structured as follows. First, it summarizes the findings in each chapter of the doctoral dissertation. Second, it discusses the main contributions. Lastly, it briefly concludes the dissertation.

Summary of the Main Findings

Chapter 1 concentrates on evaluating the effect of information dissemination in the financial markets taking a specific event as a source of information. The research questions examined in this chapter are the following:

Research question 1.1: Does the geographic proximity of information (disseminated by the Ebola outbreak events) have a statistically significant impact on the financial markets?

Research question 1.2: Is the event effect stronger for the stock returns of small companies relative to large companies?

Research question 1.3: Is the effect on the event day (i.e., day 0) larger for more volatile stocks than for less volatile stocks?

Research question 1.4: How (positively or negatively) the Ebola outbreak events affect each U.S. industry?

Research question 1.5: Are the companies exposed to intense media coverage more affected by the Ebola outbreak events than the companies receiving less media exposure?

Briefly, Chapter 1 examines whether the geographic proximity of information disseminated by the 2014–2016 Ebola outbreak events combined with intense media coverage affected stock prices in the U.S. In Chapter 1, U.S. publicly listed companies are classified depending on the exposure of their business operations. Furthermore, the Ebola outbreak events are categorized by location of their occurrence.

Chapter 1 provides evidence that that the Ebola outbreak event effect is strongest for the companies with exposure of their operations to the West African Countries region (WAC) and the U.S., for the events located in the WAC and the U.S. In addition, Chapter 1 continues investigating whether there is a difference in the magnitude of the effect in portfolios classified by capitalization size. The results confirm that the negative effect of the Ebola outbreak events is more pronounced for small securities relative to large securities. Lastly, Chapter 1 investigates whether the Ebola outbreak events affect investor sentiment proxied by the implied volatility, securities belonging to a specific industry, and securities highly exposed in the media. The results show that the effect is specifically pronounced for more volatile stocks, for the securities exposed to the intense media coverage, and for the securities belonging to the Healthcare equipment, Pharmaceutical, and Aviation industry.

Chapter 2 connects finance and politics to examine the impact of information dissemination on companies' stock returns. This chapter is built around the following research questions:

Research question 2.1: What are the factors describing the likelihood of a firm being mentioned by Trump in the period from June 2015 to June 2017?

Research question 2.2: Does the linguistic tone used in Trump's statements predict stock market returns, affects the trading volume, and the stock price volatility?

Research question 2.3: Are the political factors such as donations to certain party and business connection of a company to the presidential candidate likely to influence the stocks of the company?

More specifically, Chapter 2 evaluates President Donald J. Trump's political power on the financial markets through his social media statements around the 2016 U.S. presidential elections. The logistic regression analysis is used to investigate factors driving the likelihood of a firm being twitted or news-broadcasted by Trump around the election period.

The results suggest that Trump is more likely to cover the companies close to his knowledge, companies with which he had an established business connection, large companies, and companies with a presence on the international markets. Furthermore, the results suggest that the effect from Trump's statements made after the Election Day is negative and more pronounced than before the Election Day.

To further explain the economic impact of Trump statements Chapter 2 presents the cross-sectional regression analysis. The cross-sectional analysis includes: the timing of the statement (i.e., whether it is before or after the 2016 presidential election); the linguistic tone of the statement on the social media (i.e. negative versus non-negative); companies' size, profitability, leverage, risk level; and finally, the political orientation of the firms and their political connection to Trump. The results confirm that the political factors and companies' business connection to Trump are likely to influence companies' stocks, trading volume, and stock price volatility. The number of connection channels through which a certain company is related to Trump is also found to be a significant factor that is positively related to companies' cumulative abnormal returns.

Chapter 3 examines whether information disseminated from dramatic events, such as nuclear energy accidents, influences the U.S. financial markets. Chapter 3 is built around the following research questions:

Research question 3.1: Does the geographic proximity of information have a statistically significant impact on the financial markets, observing the stock returns of the U.S. publicly listed companies as a result to the nuclear events that took place in the U.S., France, and Japan?

Research question 3.2: Is the event effect stronger for the stock returns of small companies relative to large companies?

Research question 3.3: Do the nuclear accident events affect the implied volatility on the day of the accident?

Research question 3.4: How (positively or negatively) the nuclear accidents affect each industry?

Research question 3.5 Is there influence of the accidents that channels through the fear channel and triggers fear and bad mood among the investors, which further contributes to depressed stock prices?

More specifically, Chapter 3 documents that nuclear accident events in the period from 1944 to 2017 have statistically significant impact on the U.S. publicly listed companies. Chapter 3 tackles the problem from the behavioral finance perspective which shows that dramatic events such as a nuclear accident event can enhance fear and risk aversion among the investors and thus affect investor sentiment.

The results in this chapter show that the geographic proximity of the information to the financial markets increases the importance of the event (related to the 1944 – 2017 nuclear accidents) and its impact on companies' stock returns. Furthermore, the results show that the event effect is large, statistically significant, and negative for the U.S. companies when the nuclear accidents take place on U.S. soil - further showing stock returns reversal pattern on the first day after the event day.

Additional tests performed in Chapter 3 reveal that the impact of the nuclear accidents differ across firm size and across firm industry. Lastly, Chapter 3 finds that the implied volatility increases on the nuclear accident days; the results confirm the existence of a fear channel through which the influence of the nuclear accidents triggers fear among the investors that contributes to depressed stock prices.

Contributions

Chapter 1 primary contributions go to the field of behavioral finance. More specifically, it contributes to the literature by observing the relations between companies' exposure to different geographic regions of operation, media coverage of dramatic events, companies' size and industry of operation, fear and anxiety provoked by the events of interest, and investors' risk aversion to invest when fear and anxiety increase.

One of Chapter 1's postulate contribution is that it is fully focused on the impact of the Ebola outbreak events on the financial markets with the intent to analyze information dissemination and the importance of geographic proximity of the event. From this stand point, Chapter 1 contributes by explicitly disentangling and proportionally evaluating the events effect emitted from the three Ebola outbreak locations (WAC, U.S., and Europe) upon the companies listed on the U.S. financial markets. This chapter also, is closely related to Donadelli et al. (2016b) who analyze various globally dangerous diseases and examine their impact upon pharmaceutical companies' stock returns.

Relating to the strand of literature that examines the effect of investor sentiment on the financial markets, Chapter 1 is closely related to Kaplanski and Levy (2010a, 2010b) and Cen and Liyan-Yang (2013) and shed new light on the role of geographic proximity of information to the financial markets and its psychological effects on investors' decision making process. More explicitly, this chapter's contribution is to evaluate the balance between two contrasting effects of the Ebola outbreak events. On one side, Chapter 1 recognizes the possibility that the Ebola disease spreads fear among the general public and stock market investors, which in turn triggers a negative sentiment among most of the securities in the financial markets. On the other side, an outbreak of a disease, such as the Ebola disease, is expected to have a positive industry-specific sentiment effect on hazmat and health equipment producers, and pharmaceutical stock prices. The insights of Chapter 1 contribute by showing evidence that there is a clear relation between the relevancy of the Ebola outbreak events to investors' actions and the magnitude of the event effect.

This chapter also contributes to the literature observing the effects of media coverage on investor sentiment, by considering the geographic proximity of the information to the financial markets. The event study and cross-sectional methodology used as well as the findings in Chapter 1, relate to Fang and Peress (2009), Engelberg and Parsons (2011) and Peress (2014) who find that investors react more to media covered events and pay more attention to stocks and news/events that are closer in distance to them.

Chapter 2's central contribution to the literature draws upon providing solution and overcoming related concerns of social media's credibility of the information source. Participating in the social media is not legally monitored, thus anyone can set up an account on one of the social media platforms and anonymously share insightful information. For example, anyone can set up a Twitter account and tweet about any stock trading on the financial markets. Within those lines, information on Twitter can be intentionally or unintentionally misleading and thus of limited usefulness for conducting a valuable analysis.

Another important contribution of Chapter 2 relates to the literature examining the relation between U.S. politicians and U.S. economy and financial markets. From this stand point, Chapter 2 is related to Wagner et al. (2017) who observe expectations to realizations of President Trump's pre-election day political agenda and its post-election day effects. Chapter 2 provides valuable evidence that the financial markets reflect investor expectations on economic growth, taxes, and trade policies.

Another set of research studies (Addoum and Kumar, 2016; Julio and Yook, 2012; Boutchkova et al., 2012) to which Chapter 2 is related focus on investors' perspective, and show that investors change their portfolio compositions, companies reduce their capital investments, and stock market volatility increases before national elections. Alongside these findings, Chapter 2 contributes with suggestions that the stock market is sensitive to political news since even presidential candidates who may not be in power yet influence securities performance in terms of returns, trading volume, and stock price volatility.

President Trump brought so far unseen actions to the public political world as a role of a country leader. Regarding the literature analyzing specifically Trump's standalone actions, Chapter 2 is related to Huang and Low (2017) who simulate Donald J. Trump's communication style, appearance, and personal gestures through a Battle of the Sexes game. From this perspective, Chapter 2 contributes with results pointing to the presence of an unprecedented and unique communication style on Trump's behalf. Along those lines, Chapter 2 shows that negative linguistic tone of political speeches predicts negative stock returns.

Finally, Chapter 2 contributes to the literature analyzing connections between politicians and company executives. The results suggest that at least in the minds of investors, connections between politicians and companies' top management can be of great importance for the companies. In addition, relating to the strand of literature that examines the effect of investor sentiment on the financial markets, Chapter 2 contributions are closely related to Kaplanski and Levy (2010b) who show that certain events tend to generate negative sentiment on the days following the event day. Within those lines, this chapter sheds new light on the role of the presidential signaling and information dissemination to the financial markets, and their psychological effects on investors' decision-making process.

The contribution of Chapter 3 resides in the analysis of the impact that nuclear energy accidents have on financial markets based on a large time-span (from the year 1944 to 2017). Furthermore, it tries to evaluate the impact of these accidents on the financial markets with the intent to analyze information dissemination from different channels of influence in combination with the proximity of the event.

Regarding the literature examining the effect of investor sentiment on the financial markets, this chapter is closely in line with Kaplanski and Levy (2010a, 2010b) and Donadelli et al. (2016a) and shed light on the role of geographic proximity of information to the financial markets and its effects on investors' decision making process. The results in Chapter 3 contribute with evidence that there is a clear relation between nuclear accident events and investors' actions and the magnitude of the event effect. One of the contributions of this chapter is that it examines the role of geographic proximity of information upon three distinct samples of companies listed on the financial markets. While prior studies are pooling only the utility stocks, Chapter 3 considers two additional samples, on the one hand, nuclear energy companies, and on the other hand, companies mainly belonging to the clean energy sector. The results contribute with fresh evidence suggesting that nuclear accidents yield a decline of nuclear energy stock prices for the nuclear energy sample, whereas the clean energy stocks benefit from a nuclear accident.

Furthermore, a notable contribution of Chapter 3 to the literature is observing the effects of media coverage on investor sentiment, in combination with the geographic proximity of the information to the financial markets. The results relate to Engelberg and Parsons (2011), Peress (2014), and Donadelli (2015) who find that investors react more to media covered events and pay more attention to stocks and news/events that are closer in distance to them, as well as to the events that trigger fear among the investors.

Lastly, Chapter 3 contributes to the literature by analyzing investors' trading behavior and risk-taking attitude, and securities' implied volatility around the nuclear accident events. From this aspect, the findings relate to Baker and Wurgler (2007) and Mehra and Sah (2002) confirming the results that indeed, the fear and anxiety are in a positive relation to investor's risk-taking tendencies. In retrospective, closely related research work goes alongside Donadelli et al. (2016b) who examine whether the fear index - as a proxy for investor mood, driven by dramatic events, such as diseases, is priced in companies' stocks of certain industry; Donadelli et al. (2016b) suggest that events such as global diseases should not trigger rational trading.

Conclusion

This doctoral dissertation analyses the role and impact of information dissemination in the financial markets and specifically the effect of information dissemination upon companies' stock returns. It starts by examining whether the geographic proximity of information disseminated by the 2014–2016 Ebola outbreak events combined with intense media coverage affected stock prices in the U.S. Then, it analyses whether the effect from dramatic events (i.e. disease outbreak, nuclear energy accidents) is more pronounced for companies of certain size, for more volatile stocks, stocks of specific industry, and for stocks exposed to the intense media coverage. Next, the dissertation extends to the joint filed of politics and finance and puts effort to evaluate President Trump's political power on the financial markets through his social media statements around the 2016 U.S. presidential elections. Lastly, it concludes by observing large time span of nuclear energy accidents and further differentiating between channels through which the nuclear accidents influence the financial markets.

Notable findings to be pointed out in this dissertation are the following. First, the Ebola outbreak event effect is the strongest for the stocks of companies with exposure of their operations closer to both the birthplace of the disease as well as to the financial markets. Second, the event effect is also followed by the elevated perceived risk; that is, the implied volatility increases after the Ebola outbreak events. Third, the event effect is more pronounced for companies of small size, for more volatile stocks, stocks of specific industry, and for stocks highly covered in the media. Fourth, observing information dissemination from political figures suggest that in his public statements Trump is more likely to cover the companies close to his knowledge, companies with which he had an established business and political connection, large companies, and companies with presence on the international markets. In addition, the findings reveal that through tweeting and appearance in the news Trump can affect companies' stock outcomes, trading volume, and stock price volatility. Next, the negative linguistic tone in the disseminated information is found to lead to negative returns for the mentioned companies. Finally, the analysis presents evidence that through the "fear channel" the influence of the nuclear accidents trigger fear among the investors which then contributes to depressed stock prices.

The methodologies used in this dissertation contribute to the previous literature by filling in an important gap in this field of studies as well as provide examination of trending examples and explanations of the financial phenomena that can help industry specialists, researchers, and the general public to better understand the background of the financial markets performance.

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APPENDICES

Appendix A: Chapter 1

Table A.1 Definitions of the main variables

Variable	Variable Definitions
Total Return ($r_{i,t}$)	$r_{i,t}$ encounters for reinvesting the dividends back in the company and not distributing outside/to the shareholders.
Abnormal Return (*AR*)	*AR* is the difference between the actual rate of return of the stock considered and its ex-post expected rate of return over the whole length of the event window.
Cumulative abnormal return (*CAR*)	*CAR* is the sum of the abnormal returns over the whole length of the event window.
Event location ($EL_{l,t}$)	$EL_{l,t}$ is the event location dummy that equals 1 on the day of the event if the event occurs in the region of interest *l* (that can either be U.S. only, the WAC region, or Europe), and zero otherwise.
Monday effects ($WD_{k,t}$)	$WD_{k,t}$ is a dummy variable that equals 1 on the selected day of the week *k* (either Monday, Tuesday, Wednesday, or Thursday), and zero otherwise.
The turn-of-the-year effect (Tax_t)	*Tax*, is a dummy variable that equals 1 on the first five trading days in January, and zero otherwise.
VIX and VXO	VIX is a measure of the implied volatility of the S&P500 index option prices. VXO is a measure of implied volatility using 30-day S&P100 index option prices.
Volatility Decile	Portfolio of securities sorted in deciles by their volatility.
Size Decile	Portfolio of securities sorted in deciles by their value of capitalization.
Bid-Ask Spread	Difference between the ask and the bid prices divided by the midpoint price.
Price Range	On each day, firm's intraday high to low prices.
Trading Volume	The number of shares or contracts traded in a security or an entire market during a given period of time.

Table A.2 Disease Related News (event days)

The table reports detailed description of all 103 events taken into consideration in the 2014─2016 Ebola outbreak period. All events are sorted by type of news/event, then by date, and event location. The 103 events are later filtered to meet the non-overlapping properties as explained in Section 3. Of the total number of events, 63 are categorized as *WHO report* and 40 as *U.S. Newspapers Ebola outbreak news*. In terms of the event location, 52 events took place in the WAC region, 31 in the U.S., and 20 in Europe.

Date	Type of news/event	Event location	News' short description
June 26, 2014	WHO report	WAC	Ebola challenges West African countries as WHO ramps up response.
July 31, 2014	WHO report	WAC	WHO Director orders west African presidents to start intensified Ebola disease response plan.
August 6, 2014	WHO report	EUROPE	WHO to convene ethical review of experimental treatment for Ebola.
August 8, 2014	WHO report	WAC	1st meeting statement of the IHR Emergency Committee on the 2014 Ebola outbreak in West Africa.
August 12, 2014	WHO report	WAC	Ethical considerations for use of unregistered interventions for Ebola virus disease (EVD).
August 18, 2014	WHO report	U.S.	Release of a statement on travel and transport in relation to Ebola virus disease outbreak.
August 24, 2014	WHO report	WAC	WHO-lays off health worker receiving care after testing positive for Ebola.
August 28, 2014	WHO report	WAC	WHO issues a plan for international prevention and response to the Ebola outbreak in west Africa.
September 3, 2014	WHO report	U.S.	UN senior leaders outline needs for global Ebola response.
September 5, 2014	WHO report	WAC	Statement on the WHO Consultation on potential Ebola therapies and vaccines.
September 12, 2014	WHO report	U.S.	Remarks at an international conference: Cuban government announces substantial support to WHO Ebola response.
September 16, 2014	WHO report	U.S.	WHO welcomes the extensive Ebola support from the United States of America.
September 16, 2014	WHO report	WAC	WHO welcomes Chinese contribution of mobile laboratory and health experts for Ebola response in west Africa.
September 19,2014	WHO report	U.S.	WHO welcomes decision to establish United Nations Mission for Ebola Emergency Response.
September 22, 2014	WHO report	WAC	Study warns swift action needed to curb exponential climb in Ebola outbreak.
September 22, 2014	WHO report	WAC	Statement on the 2nd meeting of the IHR Emergency Committee regarding the 2014 Ebola outbreak in West Africa.
October 10, 2014	WHO report	EUROPE	WHO and partners agree on a common approach to strengthen Ebola preparedness in unaffected countries.
October 17, 2014	WHO report	WAC	Senegal ends Ebola transmission, WHO congratulates.
October 18, 2014	WHO report	U.S.	WHO response to internal Ebola document leaked to media.
October 20, 2014	WHO report	WAC	WHO declares end of Ebola outbreak in Nigeria.
October 23, 2014	WHO report	WAC	Statement on the 3rd meeting of the IHR Emergency Committee regarding the 2014 Ebola outbreak in West Africa.
October 24, 2014	WHO report	U.S.	WHO convenes industry leaders and key partners to discuss trials and production of Ebola vaccine.
October 28, 2014	WHO report	EUROPE	WHO welcomes Swissmedic approval of Ebola vaccine trial at Lausanne University Hospital.
October 31, 2014	WHO report	U.S.	WHO updates personal protective equipment guidelines for Ebola response.
November 6, 2014	WHO report	WAC	Senegal: WHO welcomes strong commitment from Australia to beating Ebola.
November 6, 2014	WHO report	EUROPE	WHO welcomes approval of a second Ebola vaccine trial in Switzerland.
November 7, 2014	WHO report	WAC	New WHO safe and dignified burial protocol - key to reducing Ebola transmission.

November 7, 2014	WHO report	U.S.	Statement from the Travel and Transport Task Force on Ebola virus disease outbreak in West Africa.
November 21, 2014	WHO report	WAC	WHO declares end of Ebola outbreak in the Democratic Republic of Congo.
December 2, 2014	WHO report	EUROPE	WHO congratulates Spain on ending Ebola transmission.
December 12, 2014	WHO report	EUROPE	Health partners unite to build stronger systems for health in Ebola-affected countries.
January 6, 2015	WHO report	WAC	New UNMEER chief arrives in Liberia to assess Ebola response.
January 15, 2015	WHO report	WAC	Ebola in West Africa: 12 months on.
January 18, 2015	WHO report	WAC	Government of Mali and WHO announce the end of the Ebola outbreak in Mali.
January 21,2015	WHO report	WAC	Statement on the 4th meeting of the IHR Emergency Committee regarding the 2014 Ebola outbreak in West Africa.
March 5, 2015	WHO report	WAC	Ebola vaccine efficacy trial ready to launch in Guinea.
March 10, 2015	WHO report	EUROPE	United Kingdom is declared free of Ebola virus disease.
March 11, 2015	WHO report	EUROPE	WHO and World Food program join forces to reach zero Ebola cases.
March 20, 2015	WHO report	WAC	Vaccination must be scaled up in Ebola-affected countries.
April 10, 2015	WHO report	WAC	Statement on the 5th meeting of the IHR Emergency Committee regarding the Ebola outbreak in West Africa.
May 9, 2015	WHO report	WAC	The Ebola outbreak in Liberia is over.
May 23, 2015	WHO report	EUROPE	World Health Assembly gives WHO green light to reform emergency and response program.
July 7, 2015	WHO report	WAC	Statement on the 6th meeting of the IHR Emergency Committee regarding the Ebola outbreak in West Africa.
July 31, 2015	WHO report	U.S.	World on the verge of an effective Ebola vaccine.
August 7, 2015	WHO report	WAC	An emergency within an emergency: caring for Ebola survivors.
August 14, 2015	WHO report	EUROPE	World Humanitarian Day: WHO honors health workers, calls for their protection.
August 17, 2015	WHO report	U.S.	The Ebola virus vaccine is effective. But the fight goes on.
August 31, 2015	WHO report	WAC	Guinea ring vaccination trial extended to Sierra Leone to vaccinate contacts of new Ebola case.
September 3, 2015	WHO report	WAC	Ebola transmission in Liberia is over. Nation enters 90-day intensive surveillance period.
October 5, 2015	WHO report	WAC	Statement on the 7th meeting of the IHR Emergency Committee regarding the Ebola outbreak in West Africa.
October 14, 2015	WHO report	U.S.	Preliminary study finds that Ebola virus can persist in the semen of some survivors for at least 9 months.
November 7, 2015	WHO report	WAC	Sierra Leone stops transmission of Ebola virus.
December 18, 2015	WHO report	WAC	Statement on the 8th meeting of the IHR Emergency Committee regarding the Ebola outbreak in West Africa.
December 29,2015	WHO report	WAC	End of Ebola transmission in Guinea.
January 14, 2016	WHO report	WAC	Latest Ebola outbreak over in Liberia; West Africa is at zero, but new flare-ups are likely to occur.
January 15, 2016	WHO report	WAC	New Ebola case in Sierra Leone. WHO continues to stress risk of more flare-ups.
March 17, 2016	WHO report	WAC	WHO statement on end of Ebola flare-up in Sierra Leone.
March 29, 2016	WHO report	EUROPE	WHO Director-General briefs media on outcome of Ebola Emergency Committee.
March 29, 2016	WHO report	WAC	Statement on the 9th meeting of the IHR Emergency Committee regarding the Ebola outbreak in West Africa.
April 1, 2016	WHO report	WAC	New positive case of Ebola virus disease confirmed in Liberia.
June 1, 2016	WHO report	WAC	End of Ebola transmission in Guinea.
June 9, 2016	WHO report	WAC	End of the most recent Ebola virus disease outbreak in Liberia.
July 31, 2014	U.S. news. Ebola	EUROPE	WHO Director-General, west African presidents to launch intensified Ebola outbreak response plan.

	outbreak n.		
August 2, 2014	U.S. news. Ebola outbreak n.	U.S.	American missionary aid workers infected with EVD in Liberia, Dr. Kent Brantly and Nancy Writebol, is medically evacuated to Atlanta, Georgia for treatment at Emory University Hospital.
August 21, 2014	U.S. news. Ebola outbreak n.	U.S.	The two first medically evacuated cases in the US (missionaries Nancy Writebol and Kent Brantly), having been successfully treated with the experimental therapy ZMapp, are released from Emory University Hospital free of the virus. Kent Brantly's A+ type blood was later used to treat three other cases in the United States: these included the third and fifth medically evacuated cases Rick Sacra and Ashoka Mukpo as well as the second transmitted case Nina Pham.
September 3, 2014	U.S. news. Ebola outbreak n.	U.S.	UN senior leaders outline needs for global Ebola response.
September 4, 2014	U.S. news. Ebola outbreak n.	U.S.	United States received its third medically evacuated case-a Massachusetts physician, Rick Sacra, had been working in Liberia for Serving In Mission and had performed Cesarean sections on Ebola patients before revealing symptoms. He was treated at the Nebraska Medical Center in Omaha, where he was given a blood transfusion from the first successfully recovered American patient Kent Brantly.
September 9, 2014	U.S. news. Ebola outbreak n.	U.S.	Fourth patient was removed from West Africa and placed into the United States. The doctor (whose identity has not been released) was working in Sierra Leone for the WHO and had begun treatment at Emory University Hospital. In order to recover from the virus, the patient was scheduled to receive serum from the British medically evacuated case William Pooley.
September 19, 2014	U.S. news. Ebola outbreak n.	EUROPE	WHO welcomes decision to establish United Nations Mission for Ebola Emergency Response.
September 22, 2014	U.S. news. Ebola outbreak n.	U.S.	Study warns swift action needed to curb exponential climb in Ebola outbreak.
September 24, 2014	U.S. news. Ebola outbreak n.	U.S.	The first EVD case in the United States (Thomas Eric Duncan) visits the emergency room of the Presbyterian Hospital of Dallas, where he is diagnosed with a 'low-grade, common viral disease' and sent home with antibiotics.
September 28, 2014	U.S. news. Ebola outbreak n.	U.S.	Thomas Eric Duncan is isolated at the Presbyterian Hospital of Dallas, where nurses Nina Pham and Amber Vinson are exposed to Duncan's vomit and bodily fluids. Both later become the second and third cases of EVD within the United States.
October 8, 2014	U.S. news. Ebola outbreak n.	U.S.	Thomas Eric Duncan, the first case of EVD in the U.S., dies.
October 10, 2014	U.S. news. Ebola outbreak n.	EUROPE	WHO and partners agree on a common approach to strengthen Ebola preparedness in unaffected countries.

October 15, 2014	U.S. news. Ebola outbreak n.	U.S.	A second caregiver for Thomas Eric Duncan tests positive for EVD, 29-year-old nurse Amber Vinson. The CDC seeks to track fellow airline passengers on a flight she took from Cleveland a day before being diagnosed (her trip was itself cleared by CDC personnel). The U.S. Department of Health and Human Services announced Vinson will be transferred to Emory University Hospital in Atlanta, Georgia.
October 23, 2014	U.S. news. Ebola outbreak n.	U.S.	New York City physician Craig Spencer was placed in isolation in Bellevue Hospital after experiencing symptoms of EVD. He subsequently tests positive for the Ebola virus. Spencer had returned recently from Guinea, where he had been working with Ebola patients as part of Doctors Without Borders. The diagnosis was unrelated to the cases of Ebola virus disease in Texas. Spencer completed a number of activities before arriving at the hospital, including riding the subway, visiting a bowling alley and entering another resident's car via the transportation app Uber.
October 24, 2014	U.S. news. Ebola outbreak n.	EUROPE	WHO convenes industry leaders and key partners to discuss trials and production of Ebola vaccine.
October 31, 2014	U.S. news. Ebola outbreak n.	U.S.	Maine Judge Charles C. LaVerdiere ruled that nurse Kaci Hickox (who had previously gone on a defiant bicycle ride, breaking her quarantine) must continue to undergo mandatory monitoring by public health officials, but that her movements were not to be restricted inasmuch as she was asymptomatic. "The court is fully aware that people are acting out of fear and that this fear is not entirely rational,' the judge noted.
October 31, 2014	U.S. news. Ebola outbreak n.	U.S.	WHO updates personal protective equipment guidelines for Ebola response.
November 5, 2014	U.S. news. Ebola outbreak n.	U.S.	The White House requests just over $6 billion in Ebola funding from Congress.
November 17, 2014	U.S. news. Ebola outbreak n.	U.S.	Dr. Martin Salia, Ebola infected patient, dies at the Nebraska Medical Center.
December 10, 2014	U.S. news. Ebola outbreak n.	U.S.	Time magazine names The Ebola Fighters its Person of the Year.
December 12, 2014	U.S. news. Ebola outbreak n.	EUROPE	Health partners unite to build stronger systems for health in Ebola-affected countries.
December 24, 2014	U.S. news. Ebola outbreak n.	U.S.	A CDC technician in Atlanta was potentially exposed to Ebola due to a laboratory error, and has been placed into quarantine.
January 6, 2015	U.S. news. Ebola outbreak n.	WAC	New UNMEER chief arrives in Liberia to assess Ebola response.
March 5, 2015	U.S. news. Ebola	WAC	Ebola vaccine efficacy trial ready to launch in Guinea.

	outbreak n.		
March 11, 2015	U.S. news. Ebola outbreak n.	EUROPE	WHO and World Food Programme join forces to reach zero Ebola cases.
March 20, 2015	U.S. news. Ebola outbreak n.	WAC	Vaccination must be scaled up in Ebola-affected countries.
May 23, 2015	U.S. news. Ebola outbreak n.	EUROPE	World Health Assembly gives WHO green light to reform emergency and response program.
July 31, 2015	U.S. news. Ebola outbreak n.	EUROPE	World on the verge of an effective Ebola vaccine.
August 7, 2015	U.S. news. Ebola outbreak n.	U.S.	An emergency within an emergency: caring for Ebola survivors.
August 17, 2015	U.S. news. Ebola outbreak n.	WAC	The Ebola virus vaccine is effective. But the fight goes on.
August 17, 2015	U.S. news. Ebola outbreak n.	WAC	Sierra Leone down to the last chain of Ebola virus transmission.
August 31, 2015	U.S. news. Ebola outbreak n.	WAC	Guinea ring vaccination trial extended to Sierra Leone to vaccinate contacts of new Ebola case.
October 14, 2015	U.S. news. Ebola outbreak n.	U.S.	Preliminary study finds that Ebola virus fragments can persist in the semen of some survivors for at least 9 months.
November 7, 2015	U.S. news. Ebola outbreak n.	WAC	Sierra Leone stops transmission of Ebola virus.
December 29, 2015	U.S. news. Ebola outbreak n.	WAC	End of Ebola transmission in Guinea.
January 14, 2016	U.S. news. Ebola outbreak n.	WAC	Latest Ebola outbreak over in Liberia; West Africa is at zero, but new flare-ups are likely to occur.
March 29, 2016	U.S. news. Ebola	WAC	Statement on the 9th meeting of the IHR Emergency Committee regarding the Ebola outbreak in West Africa.

	outbreak n.		
April 1, 2016	U.S. news. Ebola outbreak n.	WAC	New positive case of Ebola virus disease confirmed in Liberia.
June 1, 2016	U.S. news. Ebola outbreak n.	WAC	End of Ebola transmission in Guinea.
June 9, 2016	U.S. news. Ebola outbreak n.	WAC	End of the most recent Ebola virus disease outbreak in Liberia.

Source : http://www.who.int/mediacentre/news/ebola/press-releases/en/
http://www.lexisnexis.com.ez.statsbiblioteket.dk:2048/hottopics/lnacademic/?

Table A.3 Companies with exposure towards the WAC region

This table lists all U.S. publicly listed companies on NYSE and NASDAQ Composite which are regarded as having exposure to the WAC region. The total number of companies is 89 and it is obtained by the following selection procedure. First, I select the companies by status: I am interested in *active and publicly listed* companies. Second, I further select the companies that have a domicile in the U.S. Third, I match each company according to its *operation ownership* with the specific country or region of operation, i.e., towards WAC region. Fourth, I set up the *period of operation* of the companies from January 2014 to June 2016. The data is obtained from Bloomberg's and Bureau Van Dijk's "Orbis" databases.

NAME OF THE COMPANY		
3M COMPANY	ELI LILLY AND COMPANY	MONEYGRAM INTERNATIONAL, INC.
AGCO CORP	EMERSON ELECTRIC CO	MONSTER BEVERAGE CORPORATION
AIR PRODUCTS & CHEMICALS INC	EXTERRAN CORPORATION	NATIONAL OILWELL VARCO, INC.
ALBEMARLE CORP	GENERAC HOLDINGS INC.	NCR CORP
ALERE, INC.	GENERAL ELECTRIC COMPANY	NET 1 U.E.P.S. TECHNOLOGIES, INC.
AMERICAN TOWER CORPORATION	GREIF INC	NETAPP, INC.
AMPAL-AMERICAN ISRAEL CORPORATION	HALLIBURTON CO	NEWMARKET CORPORATION
ASHLAND INC	HARRIS CORP	NEWMONT MINING CORPORATION
ATWOOD OCEANICS INC	HERCULES OFFSHORE, INC.	OCCIDENTAL PETROLEUM CORP
AVIAT NETWORKS, INC.	HEWLETT PACKARD ENTERPRISE COMPANY	OCEANEERING INTERNATIONAL INC
BRINK'S COMPANY (THE)	HONEYWELL INTERNATIONAL INC	OVERSEAS SHIPHOLDING GROUP INC
BRISTOL-MYERS SQUIBB COMPANY	HP INC.	PARKER DRILLING CO

BRISTOW GROUP INC.	HYATT HOTELS CORPORATION	PEPSICO INC
CAL DIVE INTERNATIONAL, INC.	HYPERDYNAMICS CORPORATION	PERNIX GROUP, INC.
CATERPILLAR INC	INGRAM MICRO INC	PFIZER INC
CHEVRON CORPORATION	INGREDION INCORPORATED	PHILIP MORRIS INTERNATIONAL INC.
CISCO SYSTEMS INC	INTERNATIONAL BUSINESS MACHINES CORP	PPG INDUSTRIES INC
CITIGROUP INC	INTERPUBLIC GROUP OF COMPANIES INC	PROCTER & GAMBLE CO
COLGATE PALMOLIVE CO	JONES LANG LASALLE INC	QUINTILES TRANSNATIONAL HOLDINGS INC.
CONOCOPHILLIPS	JPMORGAN CHASE & CO	SEACOR HOLDINGS INC.
CROWN HOLDINGS, INC.	KIMBERLY CLARK CORP	SEALED AIR CORP
CSG SYSTEMS INTERNATIONAL INC	KRAFT HEINZ COMPANY (THE)	SILVER BULL RESOURCES, INC.
CUMMINS INC.	LAYNE CHRISTENSEN CO	SLOUD INC
DOW CHEMICAL COMPANY (THE)	LEVEL 3 COMMUNICATIONS, INC.	SUNERGY INC
DRIL-QUIP INC	MARATHON OIL CORPORATION	TETRA TECH INC
DUKE ENERGY CORPORATION	MARRIOTT INTERNATIONAL INC	TETRA TECHNOLOGIES INC
E. I. DU PONT DE NEMOURS AND COMPANY	MARSH & MCLENNAN COMPANIES INC	WESTERN UNION CO. (THE)
ECOLAB INC	MERCK & CO., INC.	WESCO INTERNATIONAL, INC.
TIDEWATER INC	MICROSOFT CORP	MONDELEZ INTERNATIONAL, INC.
UNITED PARCEL SERVICE INC	MINERALS TECHNOLOGIES INC	

Table A.4 Companies with exposure towards Europe

This table lists all the U.S. publicly listed companies on NYSE and NASDAQ Composite which are regarded as having exposure of their operations to Europe. The total number of companies is 309 and it is obtained by the following selection procedure. First, I select the companies by status: I am interested in *active and publicly listed* companies. Second, I further select the companies that have a domicile in the U.S. Third, I match each company according to its *operation ownership* with the specific country or region of operation i.e. towards Europe. Fourth, I set up the *period of operation* of the companies from January 2014 to June 2016. The data is obtained from Bloomberg's and Bureau Van Dijk's "Orbis" databases.

NAME OF THE COMPANY

3D SYSTEMS CORP	DISCOVERY COMM-A	LAM RESEARCH	REINSURANCE GROU
ABAXIS INC	DISNEY (WALT)-CE	LATTICE SEMICOND	REMY HOLDINGS LL
ABERCROMBIE & FI	DRIL-QUIP INC	LEAR CORP	REVLON INC-A
ABIOMED INC	ECHOSTAR CORP-A	LEVEL 3 COMM INC	RIGNET INC
ACCURAY INC	EDWARDS LIFE	LEXMARK INTL-A	RIVERBED TECHNOL
ACI WORLDWIDE IN	ELI LILLY & CO	LIBERTY PROP	ROCKWELL AUTOMAT
ACTIVISION BLIZZ	EMCOR GROUP INC	LILLY - BDR	ROFIN-SINAR TECH
AEGION CORP	ENDOLOGIX INC	LINCOLN ELECTRIC	ROWAN COMPANIE-A
ALACER GOLD -CDI	ENERSYS	LINEAR TECH CORP	RUCKUS WIRELESS
ALIGN TECHNOLOGY	ENTEGRIS INC	LITTELFUSE INC	SALESFORCE.COM
ALLEGHENY TECH	EOG RESOURCES	LIVEPERSON INC	SAMSONITE INTL
ALLERGAN INC	EPAM SYSTEMS INC	LKQ CORP	SAPIENT CORP
ALLISON TRANSMIS	EQUINIX INC	MANPOWERGROUP IN	SCHLUMBERGER LTD
ALPHABET INC-A	ESTERLINE TECH	MARRIOTT VACATIO	SCHULMAN (A)
ALTERA CORP	EVERCORE PARTN-A	MASCO CORP	SCHWEITZER-MAUDU
ALTRA INDUSTRIAL	EXLSERVICE HOLDI	MASONITE INTERNA	SEACOR HOLDINGS
AMBARELLA INC	EXPEDITORS INTL	MAXIM INTEGRATED	SEAGATE TECHNOLO
AMDOCS LTD	FACEBOOK INC-A	MCDONALDS CORP	SEALED AIR CORP
AMER EXPRESS-CED	FACTSET RESEARCH	MEASUREMENT SPEC	SEMGROUP CORP-A
AMEX-BDR	FAIRCHILD SEMICO	MEDICINES COMP	SEMTECH CORP
ANALOG DEVICES	FARO TECH	MEDIDATA SOLUTIO	SENSATA TECHNOLO
ANSYS INC	FEI COMPANY	MENTOR GRAPHICS	SERVICE CORP INT
AOL INC	FLIR SYSTEMS	MERCK & CO	SERVICENOW INC
APACHE CORP	FLUIDIGM CORP	MERIT MEDICAL	SHUTTERSTOCK INC
APPLE INC	FORD MOTOR CO	MERITOR INC	SIGNET JEWELERS
APPLIED MATERIAL	FOREST LABS INC	METTLER-TOLEDO	SIMPSON MFG
APTARGROUP INC	FOSSIL GROUP INC	MICROCHIP TECH	SIMS METAL MANAG
ARRIS GROUP INC	FREEPORT-MCMORAN	MIDDLEBY CORP	SONUS NETWORKS

ASHLAND INC	FRESH DEL MONTE	MKS INSTRUMENTS	SS&C TECHNOLOGIE
ATMEL CORP	GAMESTOP CORP-A	MOBILE MINI	ST JUDE MEDICAL
AUTOMATIC DATA	GAP INC/THE	MOLSON COORS-A	STANLEY BLACK &
AVNET INC	GENERAL MOTORS C	MONDELEZ INTER-A	STEPAN CO
AVX CORP	GENTHERM INC	MONOLITHIC POWER	STIFEL FINANCIAL
B/E AEROSPACE IN	GILEAD SCIENCES	MONOTYPE IMAGING	STRATEGIC HOTELS
BALL CORP	GLOBAL PAYMENTS	MONRO MUFFLER	SUPER MICRO COMP
BANK NY MELLON	GLOBALSTAR INC	MONSTER WORLDWID	SYKES ENTERPRISE
BAXTER INTL INC	GLOBE SPECIALTY	MORNINGSTAR INC	SYNOPSYS INC
BENCHMARK ELECTR	GOOGLE INC-A	MOTOROLA SOLUTIO	SYNTEL INC
BGC PARTNERS-A	GRAMERCY PROPERT	MSA SAFETY INC	TAKE-TWO INTERAC
BIOMARIN PHARMAC	GRAPHIC PACKAGIN	MSCI INC	TAL INTERNATIONA
BLACKROCK INC	GREENBRIER COS	NATL INSTRUMENTS	TEAM INC
BOTTOMLINE TECH	GREENHILL & CO	NEENAH PAPER INC	TECH DATA CORP
BRADY CORP - A	GT ADVANCED TECH	NETGEAR INC	TELETECH HLDGS
BRIGHT HORIZONS	GUIDEWIRE SOFTWA	NETSCOUT SYSTEMS	TENNANT CO
BRISTOL-MYER SQB	GULFMARK OFFSHOR	NEWPARK RESOURCE	TENNECO INC
BRISTOW GROUP IN	HAIN CELESTIAL	NEWPORT CORP	TERADYNE INC
BROOKFIELD OFFIC	HALLIBURTON CO	NEXTEER	TESCO CORP
BROWN & BROWN	HARMAN INTL	NIKE INC -CL B	TESLA MOTORS
CA INC	HEARTWARE INTERN	NORDSON CORP	TESSERA TECHNOL
CABLE & WIRELESS	HOLOGIC INC	NU SKIN ENTERP-A	TETRA TECHNOLOGI
CARDTRONICS INC	IGATE CORP	NVIDIA CORP	THERMON GROUP HO
CATERPILLAR INC	INFOBLOX INC	OIL STATES INTL	TIBCO SOFTWARE
CAVIUM INC	INFORMATICA CORP	OMNICOM GROUP	TIFFANY & CO
CISCO SYSTEMS	INGRAM MICRO INC	OMNIVISION TECH	TJX COS INC
CIT GROUP INC	INGREDION INC	ON SEMICONDUCTOR	TOTAL SYS SERVS
COCA-COLA ENTER	INTEGER HOLDINGS	OPKO HEALTH	TOWERS WATSON-A
COGENT COMMUNICA	INTEGRA LIFESCIE	OSHKOSH CORP	TREDEGAR CORP
COGNEX CORP	INTEGRAT DEVICE	OWENS CORNING	TRIMAS CORP
COGNIZANT TECH-A	INTEL CORP	PACCAR INC	TRONOX LTD-CL A
COLGATE-PALMOLIV	INTER PARFUMS	PALL CORP	TUPPERWARE BRAND
COMMERCIAL METAL	INTERPUBLIC GRP	PAREXEL INTL	UNISYS CORP
COMPUTER SCIENCE	INTERSIL CORP-A	PDF SOLUTIONS	UNIVERSAL CORP
COMPUWARE CORP	INTL PAPER CO	PEGASYSTEMS INC	VALEANT PHARMACE

COMSCORE INC	INTL RECTIFIER	PENSKE AUTOMOTIV	VARIAN MEDICAL S
CONCUR TECH INC	INVACARE CORP	PFIZER INC	VIRTUSA CORP
CONOCOPHILLIPS	INVESTMENT TECH	PHILIP MORRIS IN	VISA INC-BDR
CONVERSANT INC	ITT CORP	PHOTOMEDEX INC	WABCO HOLDINGS
COOPER COS INC	J2 GLOBAL INC	PLEXUS CORP	WALT DISNEY CO
COPHILLIPS - BDR	JABIL CIRCUIT	POWER INTEGRATIO	WATTS WATER TE-A
COSTAR GROUP INC	JOHN&JOHN-BDR	PRAXAIR INC	WD-40 CO
CR BARD INC	JOHNSON&JOHNSON	PROLOGIS INC	WEIGHT WATCHERS
CROCS INC	JPMORGAN CHASE	PTC INC	WHITEWAVE FOOD
CYPRESS SEMICON	KELLOGG CO	PUBLIC STORAGE	XILINX INC
DANA INC	KELLY SERVICES-A	QLIK TECHNOLOGIE	ZEBRA TECH CORP
DANAHER CORP	KENNAMETAL INC	QUIKSILVER INC	ZULILY INC -CL A
DEMANDWARE INC	KLA-TENCOR CORP	RALPH LAUREN COR	
DIEBOLD INC	KOFAX LTD	RAMBUS INC	
DIODES INC	KRATON CORP	RAYMOND JAMES	

Table A.5. Portfolios classified by exposure towards different geographic locations

The table depicts the cumulative abnormal returns (CARs) around the event day (t=0) for stocks with exposure of their operations towards the U.S., the WAC region, Europe, or All regions. CAR_{t-i} is the ith previous day cumulative abnormal rate of return and CAR_{t+i} is the ith cumulative abnormal rate of return after the determined event day. The abnormal return on day t is calculated as the difference between the observed rate of return and the ex-post expected rate of return on day t. The one-factor market model $r_{i,t} = \alpha_0 + \beta_1 r_{m,t} + \varepsilon_t$, where $r_{i,t}$ is the return on stock i in period t and $r_{m,t}$ is the S&P 500 return, is estimated using a 100-day estimation window. The two-factor market model $r_{i,t} = \alpha_0 + \beta_1 r_{m,t} + \beta_2 r_{ind,t} + \varepsilon_t$, where $r_{i,t}$ is the rate of return on stock i in period t, $r_{m,t}$ is the S&P500 rate of return, and $r_{ind,t}$ is the industry specific rate of return, is examined using line estimation method to check the robustness of the one-factor model. The first line reports the regression coefficients whereas the second line reports the corresponding t-values (in brackets). One, two, and three asterisks indicate a significance level of 10%, 5%, and 1%, respectively. The event selection procedure follows the *last/first* occurrence criteria which yield to a total number of 40 event days with non-overlapping event windows during the 2014–2016 Ebola outbreak period.

Model Type	Exposure of the company to	α_0	CAR t-5	CAR t-4	CAR t-3	CAR t-2	CAR t-1	CAR t_0	CAR t+1	CAR t+2	CAR t+3	CAR t+4.	CAR t+5	R^2
One Factor	U.S only	-0,0014 (-3,015***)	0,0020 (1,620)	-0,0027 (-0,914)	0,0028 (1,388)	-0,0043 (-1,799*)	0,0010 (3,558***)	-0,0140 (-6,114***)	-0,0062 (-1,991**)	-0,0055 (-1,655*)	-0,0011 (-2,885***)	-0,0022 (-0,541)	0,0008 (0,589)	0,3125
	WAC region	-0,0052 (-2,651***)	0,0031 (1,604)	-0,0042 (-1,110)	0,0063 (1,113)	-0,0064 (-1,887*)	0,0018 (3,293***)	-0,0198 (-2,108**)	-0,0095 (-1,702*)	-0,0076 (-1,990**)	-0,0037 (-1,842*)	-0,0038 (-1,463)	0,0019 (1,009)	0,5931
	Europe	-0,0025 (-1,964**)	0,0054 (0,441)	-0,0018 (-1,019)	0,0035 (1,200)	-0,0022 (-1,665*)	0,0011 (1,959**)	-0,0101 (-6,887***)	-0,0043 (-2,087**)	-0,0032 (-1,666*)	-0,0017 (-1,118)	0,0030 (0,554)	0,0039 (1,494)	0,7036
	All	-0,0030 (-1,997**)	0,0036 (0,071)	-0,0028 (-0,420)	0,0046 (0,532)	-0,0044 (-4,816***)	0,0013 (3,688***)	-0,0146 (-3,020***)	-0,0065 (-1,965**)	-0,0054 (-1,780*)	-0,0021 (-1,821*)	-0,0008 (-1.255)	0,0020 (0,963)	0,6031
Two Factor	U.S. only	-0,0025 (-3,669***)	0,0015 (1,632)	-0,0024 (-1,114)	0,0016 (1,566)	-0,0047 (-1,789*)	0,0010 (3,547***)	-0,0145 (-6,163***)	-0,0060 (-1,907*)	-0,0057 (-1,686*)	-0,0011 (-2,841***)	-0,0023 (-0,610)	0,0007 (0,913)	0,4036
	WAC region	-0,0061 (-2,441**)	0,0030 (1,627)	-0,0044 (-1,010)	0,0041 (1,113)	-0,0087 (-1,784*)	0,0015 (3,023***)	-0,0192 (-2,162**)	-0,0095 (-1,864*)	-0,0072 (-1,989**)	-0,0043 (-1,827*)	-0,0022 (-1,366)	0,0024 (1,018)	0,5021
	Europe	-0,0020 (-1,975**)	0,0059 (1,451)	-0,0026 (-1,273)	0,0042 (1,288)	-0,0033 (-1,661*)	0,0012 (1,999**)	-0,0135 (-6,825***)	-0,0046 (-2,257**)	-0,0029 (-1,688*)	-0,0017 (-1,709*)	0,0070 (0,544)	0,0224 (1,458)	0,7524
	All	-0,0028 (-1,983**)	0,0032 (0,059)	-0,0035 (-0,220)	0,0043 (0,212)	-0,0039 (-4,611***)	0,0012 (3,592***)	-0,0139 (-4,024***)	-0,0074 (-1,977**)	-0,0048 (-1,670*)	-0,0019 (-1,931*)	0,0031 (1,605)	0,0079 (0,902)	0,5931

Table A.6. Stocks classified by size

The table depicts the cumulative abnormal returns (CARs) around the event day (t=0) for stocks classified by size. CAR_{t-i} is the *i*th previous day cumulative abnormal rate of return and CAR_{t+i} is the *i*th cumulative abnormal rate of return after the determined event day. The abnormal return on day t is calculated as the difference between the observed rate of return and the ex-post expected rate of return on day t. The one-factor market model $r_{i,t} = \alpha_0 + \beta_1 r_{m,t} + \varepsilon_t$, where $r_{i,t}$ is the return on stock i in period t and $r_{m,t}$ is the S&P 500 return, is estimated using a 100-day estimation window. The first line reports the regression coefficients whereas the second line reports the corresponding t-values (in brackets). One, two, and three asterisks indicate a significance level of 10%, 5%, and 1%, respectively. The event selection procedure follows the *last/first* occurrence criteria which yield to a total number of 40 event days with non-overlapping event windows during the 2014–2016 Ebola outbreak period.

Size Decile	α_0	CAR_{t-5}	CAR_{t-4}	CAR_{t-3}	CAR_{t-2}	CAR_{t-1}	CAR_{t-0}	CAR_{t+1}	CAR_{t+2}	CAR_{t+3}	CAR_{t+4}	CAR_{t+5}	R^2
Decile 1 (largest firms)	-0,0032	0,0067	0,0071	0,0052	0,0065	0,0041	0,0044	-0,0042	-0,0001	0,0031	0,0021	0,0041	0,5829
	(-1,674*)	(0,874)	(0,254)	(1,479)	(1,688*)	(1,645*)	(2,450**)	(-2,430**)	(-1,912*)	(1,889*)	(0,442)	(1,088)	
Decile 2	-0,0054	0,0092	-0,0005	0,0009	-0,0013	0,0014	-0,0028	-0,0017	-0,0007	0,0018	0,0013	0,0021	0,3203
	(-1,832*)	(0,977)	(-1,498)	(1,445)	(-1,112)	(1,355)	(-3,066***)	(-2,369**)	(-1,951*)	(1,142)	(0,501)	(1,009)	
Decile 3	-0,0078	0,0049	-0,0005	0,0054	-0,0001	0,0026	-0,0025	-0,0019	-0,0003	0,0024	0,0015	0,0013	0,5053
	(-1,616)	(0,925)	(-1,544)	(1,187)	(-1,874*)	(1,844*)	(-2,145**)	(-1,688*)	(-1,877*)	(1,669*)	(0,511)	(1,397)	
Decile 4	-0,0079	0,0029	0,0015	-0,0021	-0,0024	0,0025	0	-0,0011	-0,0002	-0,0007	0,0008	0,0005	0,5849
	(-1,887*)	(0,740)	(1,641)	(-1,578)	(-1,554)	(1,014)	(1,963**)	(-2,011**)	(-1,592)	(-1,450)	(0,122)	(1,445)	
Decile 5	-0,0056	0,0035	0,0041	0,0044	-0,0019	0,0013	-0,0028	-0,0018	-0,0004	0	0,0001	0,0008	0,5728
	(-2,142**)	(1,471)	(0,556)	(1,237)	(-1,689*)	(4,213***)	(-2,558**)	(-1,963*)	(-1,250)	(0,881)	(0,280)	(1,005)	
Decile 6	-0,0064	0,0039	0,0078	0,0018	0,0049	0,0051	-0,0032	-0,0021	-0,0008	-0,0009	-0,0003	-0,0001	0,5724
	(-1,936*)	(1,562)	(1,399)	(1,105)	(1,314)	(3,980***)	(-2,562**)	(-3,884***)	(-1,659*)	(-1,551)	(-0,968)	(-1,337)	
Decile 7	-0,0055	0,0041	0,0019	0,0015	-0,0024	0,0010	-0,0035	-0,0027	-0,0013	-0,0010	-0,0004	-0,0002	0,6450
	(-1,815*)	(0,982)	(0,933)	(1,114)	(1,567)	(1,977**)	(-2,891***)	(-1,890*)	(-0,173)	(-1,411)	(-0,550)	(-0,690)	
Decile 8	-0,0039	0,0052	-0,0039	0,0012	-0,0025	0,0012	-0,0039	-0,0032	-0,0022	-0,0025	0	-0,0006	0,7363
	(-1,969**)	(0,074)	(-1,261)	(0,284)	(-1,802*)	(1,844*)	(-6,457***)	(-1,889*)	(-1,821*)	(-1,650*)	(0,477)	(-1,119)	
Decile 9	-0,0022	0,0027	-0,0026	-0,0029	0,0014	0,0023	-0,0046	-0,0042	-0,0024	-0,0019	-0,0002	-0,0001	0,6184
	(-1,682*)	(1,114)	(-1,399)	(-1,347)	(1,697*)	(1,960**)	(-3,870***)	(-4,801***)	(-1,657*)	(-1,721*)	(-0,885)	(-0,669)	
Decile 10 (smallest firms)	-0,0101	0,0072	0,0055	0,0048	-0,0011	0,0030	0,0036	-0,0091	-0,0045	-0,0051	-0,0003	-0,0002	0,5609
	(-1,743*)	(0,440)	(0,466)	(1,545)	(-1,877*)	(2,430**)	(2,871***)	(-3,873***)	(-1,997**)	(-1,981**)	(-0,688)	(-1,309)	

Table A.7. Stocks classified by volatility

The table depicts the cumulative abnormal returns (CARs) around the event day (t=0) for stocks classified by volatility. CAR_{t-i} is the *i*th previous day cumulative abnormal rate of return and CAR_{t+i} is the *i*th cumulative abnormal rate of return after the determined event day. The abnormal return on day t is calculated as the difference between the observed rate of return and the ex-post expected rate of return on day t. The one-factor market model $r_{i,t} = \alpha_0 + \beta_1 r_{m,t} + \varepsilon_t$, where $r_{i,t}$ is the return on stock i in period t and $r_{m,t}$ is the S&P 500 return, is estimated using a 100-day estimation window. The first line reports the regression coefficients whereas the second line reports the corresponding t-values (in brackets). One, two, and three asterisks indicate a significance level of 10%, 5%, and 1%, respectively. The event selection procedure follows the *last/first* occurrence criteria which yield to a total number of 40 event days with non-overlapping event windows during the 2014–2016 Ebola outbreak period.

Volatility Decile	α_0	**CAR$_{t-5}$**	**CAR$_{t-4}$**	**CAR$_{t-3}$**	**CAR$_{t-2}$**	**CAR$_{t-1}$**	**CAR$_{t-0}$**	**CAR$_{t+1}$**	**CAR$_{t+2}$**	**CAR$_{t+3}$**	**CAR$_{t+4}$**	**CAR$_{t+5}$**	**R^2**
Decile 1 (highest volatility)	-0,0084 (-2,334**)	0,0046 (1,647*)	0,0050 (1,782*)	0,0047 (1,644*)	-0,0021 (-2,012**)	0,0018 (1,967**)	-0,0069 (-2,014**)	-0,0058 (-2,503**)	-0,0033 (-1,880*)	0,0021 (1,640)	-0,0021 (-1,057)	0,0052 (1,392)	0,3209
Decile 2	-0,0087 (-2,317**)	0,0042 (1,989**)	0,0041 (1,774*)	0,0045 (1,644*)	-0,0026 (-2,014**)	0,0013 (1,714*)	-0,0046 (-1,962**)	-0,0034 (-1,709*)	-0,0012 (-2,039**)	0,0014 (2,648**)	-0,0020 (-1,021)	0,0053 (1,011)	0,6180
Decile 3	-0,0064 (-2,983***)	0,0039 (1,802*)	0,0038 (1,874*)	0,0041 (0,961)	-0,0019 (-1,967**)	0,0018 (1,801*)	-0,0042 (-2,368**)	-0,0034 (-1,774*)	-0,0009 (-1,832*)	0,0019 (1,222)	-0,0028 (-1,688*)	0,0050 (0,992)	0,6974
Decile 4	-0,0061 (-1,667*)	0,0035 (1,872*)	0,0027 (1,701*)	0,0036 (0,822)	-0,0014 (-3,116***)	0,0015 (1,991**)	-0,0033 (-4,587***)	-0,0032 (-3,111***)	-0,0005 (-1,711*)	0,0051 (0,089)	0,0026 (1,455)	0,0056 (1,144)	0,7666
Decile 5	-0,0031 (-2,552**)	0,0028 (1,654*)	0,0019 (1,847*)	0,0032 (1,334)	-0,0012 (-1,887*)	0,0020 (0,880)	-0,0028 (-7,411***)	-0,0021 (-3,457***)	-0,0005 (-1,705*)	0,0020 (1,118)	0,0017 (1,554)	0,0044 (1,599)	0,8257
Decile 6	-0,0014 (-1,968**)	0,0024 (1,660*)	0,0027 (1,280)	0,0027 (1,214)	-0,0014 (-2,604**)	0,0021 (1,187)	-0,0027 (-2,144**)	-0,0015 (-6,214***)	-0,0003 (-1,644*)	0,0015 (1,569)	0,0006 (0,989)	0,0013 (1,078)	0,8508
Decile 7	0,0003 (1,660*)	0,0019 (1,714*)	0,0017 (1,870*)	0,0022 (1,101)	-0,0013 (-4,208***)	0,0010 (1,689*)	-0,0058 (-1,562)	-0,0021 (-1,445)	0,0006 (1,201)	0,0012 (1,362)	0,0008 (1,521)	0,0008 (1,115)	0,8471
Decile 8	0,0001 (2,503**)	0,0016 (1,801*)	0,0014 (2,143**)	0,0019 (0,569)	-0,0011 (-1,772*)	0,0012 (1,892*)	-0,0021 (-1,990**)	-0,0019 (-5,118***)	0,0004 (1,874*)	0,0011 (0,693)	0,0009 (1,087)	0,0006 (1,236)	0,8239
Decile 9	0,0012 (3,647***)	0,0012 (1,967**)	0,0019 (2,982***)	0,0020 (1,997**)	-0,0014 (-1,200)	0,0004 (1,774*)	-0,0016 (-2,996***)	-0,0011 (-6,554***)	-0,0002 (-4,128***)	0,0006 (2,441**)	0,0003 (2,501**)	0,0002 (1,366)	0,4911
Decile 10 (lowest volatility)	0,0008 (4,585***)	0,0013 (1,664*)	0,0026 (2,114**)	0,0013 (2,881***)	-0,0010 (-2,114**)	0,0006 (1,992**)	-0,0016 (-6,002***)	-0,0005 (-1,740*)	-0,0007 (-2,119**)	0,0007 (2,331**)	0,0016 (2,211**)	0,0012 (1,366)	0,3515

Table A.8. Event effect on U.S. Industries

The table depicts the cumulative abnormal returns (CARs) around the event day (t=0) for stocks classified by industry of operation. CAR_{t-i} is the *i*th previous day cumulative abnormal rate of return and CAR_{t+i} is the *i*th cumulative abnormal rate of return after the determined event day. The abnormal return on day t is calculated as the difference between the observed rate of return and the ex-post expected rate of return on day t. The one-factor market model $r_{i,t} = \alpha_0 + \beta_1 r_{m,t} + \varepsilon_t$, where $r_{i,t}$ is the return on stock i in period t and $r_{m,t}$ is the S&P 500 return, is estimated using a 100-day estimation window. The first line reports the regression coefficients whereas the second line reports the corresponding t-values (in brackets). One, two, and three asterisks indicate a significance level of 10%, 5%, and 1%, respectively. The event selection procedure follows the *last/first* occurrence criteria which yield to a total number of 40 event days with non-overlapping event windows during the 2014–2016 Ebola outbreak period. Industries have been selected by their contribution to U.S. GDP. Below presented, are the 12 largest by contribution industries according to S&P Dow Jones Industry Indexes.

Industry name	α_0	CAR_{t-5}	CAR_{t-4}	CAR_{t-3}	CAR_{t-2}	CAR_{t-1}	CAR_{t-0}	CAR_{t+1}	CAR_{t+2}	CAR_{t+3}	CAR_{t+4}	CAR_{t+5}	R^2
Capital Markets	-0,0063 (-2,221**)	0,0026 (0,777)	0,0024 (0,045)	0,0083 (0,158)	0,0047 (0,048)	0,0051 (2,059**)	-0,0034 (-2,094**)	-0,0032 (-1,694*)	-0,0024 (-1,923*)	-0,0013 (-1,679*)	0,0002 (1,571)	0,0011 (1,445)	0,6619
Healthcare Equipment	0,0042 (1,886*)	0,0035 (1,652*)	0,0057 (0,063)	0,0025 (1,657*)	0,0037 (1,731*)	0,0035 (2,020**)	0,0103 (1,993**)	0,0093 (2,442**)	0,0066 (1,732*)	0,0046 (0,896)	0,0032 (0,046)	0,0055 (0,138)	0,5092
Crude Oil	-0,0072 (-1,642)	-0,0036 (-2,173**)	-0,0030 (-2,357**)	-0,0013 (-1,889*)	-0,0003 (-1,685*)	0,0001 (2,064*)	-0,0061 (-3,012***)	-0,0064 (-1,712*)	-0,0042 (-1,815*)	-0,0033 (-0,162)	-0,0013 (-0,643)	-0,0022 (-1,827*)	0,2076
Industrials	-0,0049 (-3,632***)	-0,0091 (-1,697*)	-0,0073 (-0,251)	-0,0013 (-1,642)	-0,0016 (-1,011)	0,0025 (1,646*)	-0,0060 (-1,972**)	-0,0062 (-2,024**)	-0,0037 (-2,348**)	-0,0021 (-1,655*)	0,0013 (1,481)	0,0010 (1,324)	0,7649
Materials	-0,0010 (-1,821*)	-0,0038 (-1,950*)	-0,0036 (-1,666*)	-0,0023 (-2,071**)	-0,0026 (-1,998**)	-0,0005 (-2,003**)	-0,0055 (-1,994**)	-0,0053 (-1,817*)	-0,0046 (-1,652*)	-0,0022 (-1,644*)	-0,0012 (-0,569)	0,0005 (1,639)	0,6703
Information Technology	0,0053 (2,014**)	-0,0021 (-0,378)	0,0032 (1,277)	-0,0005 (-1,114)	-0,0023 (-1,980**)	-0,0013 (1,652*)	-0,0047 (-2,014**)	-0,0048 (-1,698*)	-0,0022 (-2,347**)	-0,0011 (-1,640)	-0,0007 (-2,116**)	-0,0024 (-1,489)	0,8014
Utilities	-0,0021 (-0,855)	0,0022 (0,598)	0,0017 (1,812*)	-0,0024 (-1,690*)	-0,023 (-1,245)	0,0014 (1,964**)	-0,0046 (-1,980**)	-0,0022 (-2,650***)	-0,0019 (-1,871*)	-0,0027 (-1,965**)	-0,0016 (-1,391)	0,0007 (0,806)	0,1298
Energy	-0,0061 (-3,241***)	-0,0024 (-1,763*)	-0,0038 (-0,412)	-0,0054 (-1,968**)	-0,0043 (-2,890***)	-0,0014 (-1,706*)	-0,0070 (-2,396**)	-0,0031 (1,658*)	-0,0020 (1,874*)	-0,0042 (-1,812*)	0,0006 (1,646*)	0,0008 (1,349)	0,5152
Food & Beverage	0,0013 (4,014***)	-0,0011 (-0,054)	-0,0033 (-1,240)	-0,0012 (-1,492)	-0,007 (-1,732*)	0,0025 (1,908*)	0,0052 (1,997**)	0,0061 (1,989**)	0,0059 (1,732*)	0,0011 (0,564)	0,0022 (1,954*)	-0,0006 (-1,498)	0,5457
Aviation	-0,0064 (-2,879***)	0,0008 (1,241)	0,0038 (0,561)	0,0029 (1,328)	0,0033 (0,336)	-0,0002 (-1,919*)	-0,0091 (-1,978**)	-0,0061 (-2,647***)	-0,0049 (-1,654*)	0,0016 (1,640)	0,0045 (1,870*)	0,0036 (0,198)	0,5612
Pharma.	0,0031 (3,009***)	0,0029 (1,701*)	0,0027 (1,687*)	0,0025 (1,698*)	0,0015 (1,287)	0,0013 (1,914*)	0,0050 (1,899*)	0,0052 (2,698***)	0,0056 (2,344**)	0,0027 (1,485)	0,0015 (0,655)	0,0018 (0,221)	0,4304
Biotech.	0,0046 (2,573**)	0,0026 (1,882*)	0,0025 (1,714*)	0,0015 (1,645*)	0,0017 (1,332)	0,0014 (2,122**)	0,0067 (2,102**)	0,0060 (1,997**)	0,0063 (2,977***)	0,0053 (3,145***)	0,0060 (0,540)	0,0042 (1,115)	0,2911

Table A.9. Intense media coverage effects on company securities

The table depicts the cumulative abnormal returns (CARs), trading volume, price range, and bid-ask spread around the event day (t=0) for the events and stocks undergoing high intensity of media coverage. I use the number as well as the frequency of newspaper articles published about that stock in the media and I refer to the LexisNexis "relevance score" to measure the quality of matching of an article to a specific company or stock. I use LexisNexis frequency of publishing score of 70% or above as a threshold to distinguish between the stocks and events heavily covered in the media from the ones that are less covered . CAR_{t-i}; Vol_{t-i} ; $Range_{t-i}$; $Bid - Ask_{t-i}$ are the *i*th previous day abnormal rates and CAR_{t+i}; Vol_{t+i} ; $Range_{t+i}$; $Bid - Ask_{t+i}$ are the abnormal rates on the day after the determined event day. The second line reports the corresponding t-values (in brackets). One, two, and three asterisks indicate a significance level of 10%, 5%, and 1%, respectively. The event selection procedure follows the *last/first* occurrence criteria which yield to a total number of 40 event days with non-overlapping event windows during the 2014-2016 Ebola outbreak period.

Cumulative Abnormal Return

α_0	CAR_{t-5}	CAR_{t-4}	CAR_{t-3}	CAR_{t-2}	CAR_{t-1}	CAR_{t_0}	CAR_{t+1}	CAR_{t+2}	CAR_{t+3}	CAR_{t+4}	CAR_{t+5}	R^2
-0,0022 (-1,997**)	0,0089 (1,555)	-0,0049 (-1,617)	0,0114 (1,147)	-0,0010 (-1,885*)	0,0043 (1,915*)	-0,0388 (-2,668***)	-0,0163 (-4,125***)	-0,0134 (-2,668***)	-0,0053 (-1,983**)	0,0013 (1,715*)	0,0130 (1,482)	0,4035

Volume

α_0	Vol_{t-5}	Vol_{t-4}	Vol_{t-3}	Vol_{t-2}	Vol_{t-1}	Vol_{t_0}	Vol_{t+1}	Vol_{t+2}	Vol_{t+3}	Vol_{t+4}	Vol_{t+5}	R^2
0,0059 (1,877*)	0,0148 (1,039)	0,0180 (1,559)	-0,0277 (-1,005)	-0,0091 (-0,889)	-0,0220 (-1,991**)	0,0557 (3,668***)	0,0547 (2,889***)	0,0481 (3,457***)	0,0426 (1,915*)	0,0240 (1,119)	0,0230 (1,470)	0,5611

Range

α_0	$Range_{t-5}$	$Range_{t-4}$	$Range_{t-3}$	$Range_{t-2}$	$Range_{t-1}$	$Range_{t\_0}$	$Range_{t+1}$	$Range_{t+2}$	$Range_{t+3}$	$Range_{t+4}$	$Range_{t+5}$	R^2
0,0027 (6,224***)	0,0370 (1,185)	0,0280 (1,199)	0,0362 (1,333)	0,0493 (1,969**)	0,0312 (5,510***)	0,0700 (2,334**)	0,0674 (1,992**)	0,0515 (2,254**)	0,0450 (1,648*)	0,0282 (1,863*)	0,0299 (1,265)	0,3877

Bid-Ask Spread

α_0	Bid-Ask_{t-5}	Bid-Ask_{t-4}	Bid-Ask_{t-3}	Bid-Ask_{t-2}	Bid-Ask_{t-1}	Bid-Ask_{t_0}	Bid-Ask_{t+1}	Bid-Ask_{t+2}	Bid-Ask_{t+3}	Bid-Ask_{t+4}	Bid-Ask_{t+5}	R^2
0,0163 (2,005**)	0,0301 (1,587)	0,0320 (1,485)	0,0392 (1,489)	0,0541 (2,101**)	0,0354 (1,989**)	0,0602 (3,665***)	0,0473 (2,114**)	0,0345 (1,885*)	0,0031 (1,736*)	0,0370 (1,8963*)	0,0342 (1,223)	0,4522

Table A.9.1 Event Study - cumulative average abnormal return results

The table depicts the cumulative average abnormal returns (CARs) around the event day ($\boldsymbol{t}$=0) for portfolios of companies categorized by exposure towards different geographic locations, by size, level of stock's volatility, industry of operation, and intensity of events' media coverage. The abnormal return on day $\boldsymbol{t}$ is calculated as the difference between the observed rate of return and the ex-post expected rate of return on day $\boldsymbol{t}$. The one-factor market model $\boldsymbol{r_{it}} = \boldsymbol{\alpha_0} + \boldsymbol{\beta_1 r_{m,t}} + \boldsymbol{\varepsilon_t}$, where $\boldsymbol{r_{it}}$ is the return on stock $\boldsymbol{i}$ in period $\boldsymbol{t}$ and $\boldsymbol{r_{m,t}}$ is the S&P 500 return, is estimated using a 100-day estimation window. The event selection procedure follows the *last/first* occurrence criteria which yields to a total number of 40 event days with non-overlapping event windows during the 2014–2016 Ebola outbreak period

Event Window	No. of non-overlapping events	CAR (%)	t-value
Panel 1. Portfolios classified by exposure towards			
All regions			
[-5,+5]	40	-1.228	-1.676*
[0, +1]	40	-1.055	-2.002**
[0, +5]	40	-0.456	-1.975**
U.S. only			
[-5,+5]	10	-1.400	-6.114***
[0, +1]	10	-0.590	-2.101**
[0, +5]	10	-0.970	-1.646*
WAC region			
[-5,+5]	21	-1.980	-2.108**
[0, +1]	21	-1.465	-2.050**
[0, +5]	21	-0.708	-1.982**
Europe			
[-5,+5]	9	-1.010	-6.887***
[0, +1]	9	-0.720	-1.983**
[0, +5]	9	-0.206	-2.155**
Panel 2. Stocks classified by size			
Decile 1			
[-5,+5]	40	0.670	1.622
[0, +1]	40	-0.510	-1.058
[0, +5]	40	-0.156	-1.685*
Decile 10			
[-5,+5]	40	0.034	1.529
[0, +1]	40	-0.275	-2.432**
[0, +5]	40	-0.260	-1.993**
Panel 3. Stocks classified by volatility			
Decile 1			
[-5,+5]	40	0.029	1.584
[0, +1]	40	-0.635	-2.347**
[0, +5]	40	-0.180	-2.005**
Decile 10			
[-5,+5]	40	0.050	1.021
[0, +1]	40	-0.105	-1.710*
[0, +5]	40	0.011	1.129
Panel 4. Event effect on U.S. industries			
Healthcare equipment			
[-5,+5]	40	0.530	2.124**
[0, +1]	40	0.980	2.332**
[0, +5]	40	0.658	1.998**
Aviation			
[-5,+5]	40	-0.018	-1.074
[0, +1]	40	-0.760	-1.969**
[0, +5]	40	-0.173	-1.848*
Panel 5. Intensity of media coverage			
Intense coverage			
[-5,+5]	40	-0.370	-1.996**
[0, +1]	40	-2.755	-2.668***
[0, +5]	40	-0.991	-2.586***
No coverage			
[-5,+5]	40	-0.228	-1.676*
[0, +1]	40	-1.055	-2.002**
[0, +5]	40	-0.456	-1.975**
Panel 6. Abnormal volume, Price range and Bid-Ask spread			
Volume			

[-5,+5]	40	2.010	2.132**
[0, +1]	40	5.520	2.624***
[0, +5]	40	4.135	2.211**
Range			
[-5,+5]	40	4.306	1.968**
[0, +1]	40	6.870	3.018***
[0, +5]	40	4.866	2.215**
Bid-Ask			
[-5,+5]	40	3.700	2.263**
[0, +1]	40	5.375	3.368***
[0, +5]	40	3.605	2.003**

Table A.10. Geographic proximity effect on financial markets – controlling for reversal effects
The table reports the results of the following regression:

$$r_{i,t} = \gamma_0 + \sum_{j=1}^{5} \gamma_{1,i} r_{i,t-j} + \sum_{k=1}^{4} \gamma_{2,k} WD_{k,t} + \gamma_3 Tax_t + \sum_{l=0}^{5} \gamma_{4,l} E_{l,t} + \epsilon_t$$

where $r_{i,t}$ is the rate of return of stock i on day t with exposure of its operations towards the U.S., the WAC region, Europe, or All regions, γ_0 is the regression intercept, $r_{i,t-j}$ is the lagged dependent variable—the *j*th previous day rate of return, $WD_{k,t}$ with $k = 1, \dots, 4$ are dummy variables for the day of the week (Monday, Tuesday, Wednesday, and Thursday), Tax_t is a dummy variable for the first five days of the taxation year, and $E_{l,t}$ with $l = 0 \dots 5$, stands for possible event effect and reversal effect indicator. The events occurred during the 2014–2016 Ebola outbreak period (3-year period) and include a total number of 103 event days of the disease outbreak. From the total number of events, 52 took place in the WAC region, 31 in the U.S., and 20 in Europe. Panel A depicts the regression results including the control variables whereas Panel B depicts the regression results without the control variables. The first line reports the regression coefficients whereas the second line reports the corresponding t-values (in brackets). One, two, and three asterisks indicate a significance level of 10%, 5%, and 1%, respectively.

Exposure of the company to	γ_0	R_{t-5}	R_{t-4}	R_{t-3}	R_{t-2}	R_{t-1}	Mon.	Tue.	Wed.	Thu.	Tax	$E_{t,0}$	$E_{t,1}$	$E_{t,2}$	$E_{t,3}$	$E_{t,4}$	$E_{t,5}$	R^2
PANEL A: Regression results including the control variables																		
U.S. only	-0,0158 (-3,132***)	0,0220 (1,636)	-0,0144 (-0,900)	0,0245 (1,376)	-0,0120 (-1,791*)	0,0119 (3,242***)	-0,0321 (-1,980**)	-0,0108 (-1,298)	-0,0464 (-0,009)	-0,0541 (-1,295)	0,0305 (1,979**)	-0,0230 (-6,264***)	-0,0192 (-1,987**)	-0,0155 (-1,632*)	-0,0112 (-2,851***)	-0,0102 (-0,541)	0,0120 (0,589)	0,4732
WAC region	-0,0413 (-2,761***)	0,0351 (1,616)	-0,0145 (-1,121)	0,0261 (1,132)	-0,0172 (-1,870*)	0,0183 (3,182***)	-0,0342 (-1,695*)	-0,0402 (-0,729)	-0,0801 (-0,127)	-0,0522 (-1,007)	0,0216 (1,673*)	-0,0278 (-2,129**)	-0,0201 (-1,750*)	-0,0163 (-1,987**)	-0,0125 (-1,812*)	-0,0113 (-1,407)	0,0135 (1,119)	0,5220
Europe	-0,0141 (-1,962**)	0,0240 (0,431)	-0,0123 (-1,012)	0,0205 (1,220)	-0,0112 (-1,668*)	0,0112 (1,939**)	-0,0281 (-1,684*)	-0,0102 (-1,106)	0,0359 (0,918)	-0,0516 (-1,227)	0,0250 (1,734*)	-0,0195 (-6,967***)	-0,0143 (-2,125**)	-0,0139 (-1,660*)	-0,0107 (-1,028)	-0,0052 (-0,542)	0,0025 (1,404)	0,6624
All	-0,0208 (-1,987**)	0,0314 (0,041)	-0,0128 (-0,310)	0,0226 (0,583)	-0,0148 (-4,312***)	0,0116 (3,581***)	-0,0312 (-2,231**)	-0,0254 (-1,296)	0,0454 (0,058)	-0,0470 (-1,326)	0,0288 (1,852*)	-0,0225 (-3,521***)	-0,0162 (-1,967**)	-0,0143 (-1,788*)	-0,0122 (-1,834*)	0,0111 (1,263)	0,0114 (0,955)	0,6032
PANEL B: Regression results without the control variables																		
U.S. only	-0,0123 (-3,328***)											-0,0244 (-6,231***)	-0,0169 (-1,827*)	-0,0157 (-1,646*)	-0,0115 (-2,742***)	-0,0123 (-0,625)	0,0127 (0,903)	0,4336
WAC region	-0,0402 (-2,317**)											-0,0262 (-2,155**)	-0,0195 (-1,880*)	-0,0172 (-1,999**)	-0,0123 (-1,866*)	-0,0110 (-1,346)	0,0121 (1,215)	0,5169
Europe	-0,0119 (-1,964**)											-0,0185 (-6,212***)	-0,0146 (-2,269**)	-0,0129 (-1,671*)	-0,0109 (-1,723*)	-0,0062 (-0,442)	0,0014 (1,455)	0,6538
All	-0,0267 (-1,971**)											-0,0229 (-4,011***)	-0,0172 (-1,967**)	-0,0138 (-1,665*)	-0,0113 (-1,925*)	-0,0101 (-1,621)	0,0103 (0,202)	0,6461

Table A.11. Stocks classified by size - controlling for reversal effects

The table reports the results of the following regression:

$$r_{i,t} = \gamma_0 + \sum_{j=1}^{5} \gamma_{1,i} r_{i,t-j} + \sum_{k=1}^{4} \gamma_{2,k} WD_{k,t} + \gamma_3 Tax_t + \sum_{l=0}^{5} \gamma_{4,l} E_{l,t} + \epsilon_t$$

where $r_{i,t}$ is the rate of return of stock i on day t classified by size, γ_0 is the regression intercept, $r_{i,t-j}$ is the lagged dependent variable—the jth previous day rate of return, $WD_{k,t}$ with $k = 1, \dots, 4$ are dummy variables for the day of the week (Monday, Tuesday, Wednesday, and Thursday), Tax_t is a dummy variable for the first five days of the taxation year, and $E_{l,t}$ with $l = 0 \dots 5$, stands for possible event effect and reversal effect indicator. The events occurred during the 2014–2016 Ebola outbreak period (3-year period) and include a total number of 103 event days of the disease outbreak. From the total number of events, 52 took place in the WAC region, 31 in the U.S., and 20 in Europe. The first line reports the regression coefficients whereas the second line reports the corresponding t-values (in brackets). One, two, and three asterisks indicate a significance level of 10%, 5%, and 1%, respectively.

Size Decile	γ_0	R_{t-5}	R_{t-4}	R_{t-3}	R_{t-2}	R_{t-1}	Mon.	Tue.	Wed.	Thu.	Tax	$E_{t,0}$	$E_{t,1}$	$E_{t,2}$	$E_{t,3}$	$E_{t,4}$	$E_{t,5}$	R^2
Decile 1 (largest firms)	-0,0323 (-1,675*)	0,0672 (0,832)	0,0712 (0,251)	0,0521 (1,480)	0,0659 (1,665*)	0,0114 (1,643*)	-0,0182 (-1,973**)	0 (0,021)	-0,0091 (-0,223)	-0,0015 (-0,593)	0,0314 (1,979**)	-0,0142 (-2,230**)	-0,0140 (-2,331**)	-0,0138 (-1,221)	-0,0131 (-1,877*)	-0,0121 (-1,442)	-0,0207 (-1,038)	0,2829
Decile 2	-0,0542 (-1,832*)	0,0924 (0,447)	-0,0053 (-1,448)	0,0092 (1,462)	-0,0138 (-1,123)	0,0145 (1,345)	-0,0224 (-2,634***)	0,0110 (1,134)	-0,0072 (-0,123)	-0,0073 (-0,431)	0,0283 (1,645*)	-0,0281 (-3,001***)	-0,0267 (-2,220**)	-0,0173 (-1,921*)	-0,0128 (-1,142)	-0,0103 (-1,301)	-0,0201 (-1,012)	0,4203
Decile 3	-0,0781 (-1,613)	0,0496 (0,900)	-0,0055 (-1,546)	0,0543 (1,144)	-0,0017 (-1,893*)	0,0264 (1,674*)	-0,0246 (-2,013**)	0,0794 (0,053)	0,0165 (0,222)	-0,0093 (-1,344)	0,0230 (1,744*)	-0,0254 (-2,235**)	-0,0239 (-1,677*)	-0,0132 (-1,866*)	-0,0124 (-1,648*)	0,0205 (1,215)	-0,0103 (-0,337)	0,3053
Decile 4	-0,0790 (-1,885*)	0,0298 (0,449)	0,0157 (1,640)	-0,0214 (-1,526)	-0,0246 (-1,541)	0,0255 (1,214)	-0,0159 (-1,667*)	0,0291 (0,076)	0,0084 (1,236)	-0,0031 (-0,123)	0,0289 (1,852*)	0 (1,961**)	-0,0110 (-2,011**)	-0,0102 (-1,824*)	-0,0107 (-1,441)	0,0108 (0,101)	0,0200 (1,045)	0,2849
Decile 5	-0,0531 (-2,135**)	0,0351 (1,432)	0,0419 (0,346)	0,0446 (1,204)	-0,0195 (-1,674*)	0,0134 (2,213**)	-0,0280 (-1,857*)	0,0553 (0,120)	0,0068 (1,825)	-0,0095 (-1,522)	0,0215 (1,887*)	-0,0284 (-2,128**)	-0,0281 (-1,683*)	-0,0145 (-1,213)	0 (0,221)	0,0101 (0,282)	0,0128 (1,025)	0,1738
Decile 6	-0,0647 (-1,942*)	0,0393 (1,571)	0,0780 (1,392)	0,0188 (1,182)	0,0494 (1,356)	0,0115 (2,460**)	-0,0317 (-1,699*)	-0,0452 (-0,137)	0,0094 (1,104)	-0,0126 (-0,153)	0,0200 (1,837*)	-0,0325 (-2,562**)	-0,0321 (-2,264**)	-0,0181 (-1,655*)	-0,0149 (-1,581)	-0,0103 (-0,902)	-0,0199 (-1,328)	0,4704
Decile 7	-0,0552 (-1,823*)	0,0415 (0,132)	0,0192 (0,912)	0,0160 (1,131)	-0,0243 (-1,567)	0,0103 (1,968**)	-0,0334 (-2,322**)	0,0554 (0,342)	0,0076 (0,052)	-0,0014 (-0,382)	0,0195 (1,981**)	-0,0353 (-2,321***)	-0,0327 (-1,970*)	-0,0113 (-0,103)	-0,0110 (-1,211)	-0,0134 (-0,542)	-0,0322 (-1,290)	0,4420
Decile 8	-0,0396 (-1,967**)	0,0527 (0,034)	-0,0394 (-1,273)	0,0172 (0,226)	-0,0252 (-1,870*)	0,0126 (1,867*)	-0,0303 (-1,756*)	-0,0236 (-0,371)	-0,0033 (-1,246)	-0,0089 (-0,453)	0,0147 (1,693*)	-0,0396 (-6,234***)	-0,0324 (-1,821*)	-0,0292 (-1,821*)	-0,0225 (-1,660*)	0 (0,454)	-0,0306 (-1,120)	0,3163
Decile 9	-0,0222 (-1,688*)	0,0279 (1,128)	-0,0266 (-1,391)	-0,0293 (-1,347)	0,0141 (1,688*)	0,0238 (1,966**)	-0,0422 (-1,649*)	-0,0222 (-0,110)	-0,0063 (-1,113)	-0,0041 (-1,401)	0,0152 (1,711*)	-0,0463 (-3,972***)	-0,0421 (-2,509**)	-0,0414 (-1,687*)	-0,0429 (1,811*)	-0,0322 (-0,485)	-0,0323 (-1,207)	0,1184
Decile 10 (smallest firms)	-0,0332 (-1,752*)	0,0281 (0,493)	0,0558 (0,467)	0,0484 (1,566)	-0,0243 (-1,871*)	0,0309 (2,430**)	-0,0478 (-2,225**)	-0,0426 (-1,482)	-0,0091 (-0,934)	-0,0055 (-0,541)	0,0121 (1,842*)	-0,0525 (-2,939***)	-0,0524 (-2,142**)	-0,0425 (-1,980**)	-0,0391 (-1,971**)	-0,0303 (-1,128)	-0,0527 (-1,323)	0,2460

Table A.12. Stocks classified by volatility - controlling for reversal effects

The table reports the results of the following regression:

$$r_{i,t} = \gamma_0 + \sum_{j=1}^{5}\gamma_{1,i}r_{i,t-j} + \sum_{k=1}^{4}\gamma_{2,k}WD_{k,t} + \gamma_3 Tax_t + \sum_{l=0}^{5}\gamma_{4,l}E_{l,t} + \epsilon_t$$

where $r_{i,t}$ is the rate of return of stock i on day t classified by volatility, γ_0 is the regression intercept, $r_{i,t-j}$ is the lagged dependent variable—the jth previous day rate of return, $WD_{k,t}$ with $k = 1, \dots, 4$ are dummy variables for the day of the week (Monday, Tuesday, Wednesday, and Thursday), Tax_t is a dummy variable for the first five days of the taxation year, and $E_{l,t}$ with $l = 0 \dots 5$, stands for possible event effect and reversal effect indicator. The events occurred during the 2014–2016 Ebola outbreak period (3-year period) and include a total number of 103 event days of the disease outbreak. From the total number of events, 52 took place in the WAC region, 31 in the U.S., and 20 in Europe. The first line reports the regression coefficients, while the second line reports the corresponding t-values (in brackets). One, two, and three asterisks indicate a significance level of 10%, 5%, and 1%, respectively.

Volatility Decile	γ_0	R_{t-5}	R_{t-4}	R_{t-3}	R_{t-2}	R_{t-1}	Mon.	Tue.	Wed.	Thu.	Tax	$E_{t,0}$	$E_{t,1}$	$E_{t,2}$	$E_{t,3}$	$E_{t,4}$	$E_{t,5}$	R^2
Decile 1 (highest volatility)	-0,0842 (-2,134**)	0,0146 (1,657*)	0,0150 (1,732*)	0,0147 (1,656*)	-0,0131 (-2,321**)	0,0018 (1,967**)	-0,0146 (-1,669*)	-0,0132 (-1,732*)	-0,0124 (-0,501)	-0,0122 (-1,312)	0,0127 (1,965**)	-0,0522 (-2,221**)	-0,0519 (-2,521**)	-0,0413 (-1,810*)	0,0321 (1,647*)	-0,0221 (-1,557)	0,0163 (0,342)	0,3232
Decile 2	-0,0873 (-2,327**)	0,0142 (1,969**)	0,0141 (1,764*)	0,0145 (1,646*)	-0,0126 (-2,025**)	0,0013 (1,714*)	-0,0143 (-2,100**)	-0,0127 (-1,754*)	-0,0122 (-0,627)	-0,0115 (-0,525)	0,0121 (1,896*)	-0,0486 (-1,967**)	-0,0434 (-1,751*)	-0,0412 (-2,032**)	0,0314 (1,648*)	-0,0220 (-0,031)	0,0153 (1,005)	0,6121
Decile 3	-0,0646 (-2,934***)	0,0139 (1,822*)	0,0138 (1,834*)	0,0141 (0,991)	-0,0119 (-1,978**)	0,0018 (1,801*)	-0,0144 (-1,675*)	-0,0127 (-1,669*)	-0,0123 (-0,601)	-0,0113 (-1,426)	0,0119 (1,742*)	-0,0442 (-2,252**)	-0,0434 (-1,774*)	-0,0339 (-1,812*)	0,0319 (1,522)	-0,0228 (-1,688*)	0,0150 (1,092)	0,2174
Decile 4	-0,0614 (-1,677*)	0,0135 (1,852*)	0,0127 (1,761*)	0,0136 (1,142)	-0,0114 (-3,226***)	0,0015 (1,991**)	-0,0131 (-1,656*)	-0,0113 (-1,954*)	-0,0119 (-0,541)	-0,0112 (-0,389)	0,0117 (1,942**)	-0,0433 (-2,145**)	-0,0431 (-3,871***)	-0,0315 (-1,714*)	0,0251 (1,082)	0,0216 (2,455)	0,0156 (1,184)	0,3245
Decile 5	-0,0312 (-2,552**)	0,0128 (1,664*)	0,0119 (1,887*)	0,0132 (0,324)	-0,0112 (-1,932*)	0,0020 (0,880)	-0,0129 (-1,881*)	-0,0111 (-1,238)	-0,0115 (-0,231)	-0,0108 (-1,358)	0,0111 (1,716*)	-0,0358 (-2,411**)	-0,0321 (-3,466***)	-0,0305 (-1,755*)	0,0220 (1,150)	0,0217 (1,532)	0,0144 (0,509)	0,4157
Decile 6	-0,0145 (-1,962**)	0,0124 (1,664*)	0,0137 (1,280)	0,0127 (0,202)	-0,0114 (-2,643**)	0,0021 (1,187)	-0,0118 (-1,647*)	-0,0107 (-0,025)	-0,0110 (-0,019)	-0,0108 (-0,354)	0,0112 (1,645*)	-0,0271 (-2,152**)	-0,0255 (-6,110***)	-0,0278 (-1,648*)	0,0215 (0,541)	0,0106 (1,149)	0,0113 (1,041)	0,1208
Decile 7	0,0134 (1,650*)	0,0119 (1,723*)	0,0117 (1,872*)	0,0122 (1,251)	-0,0113 (-4,119***)	0,0010 (1,689*)	-0,0119 (-1,709*)	-0,0105 (-1,051)	-0,0108 (-0,864)	-0,0106 (-1,048)	0,0107 (1,999**)	-0,0258 (-1,552)	-0,0221 (-1,450)	0,0256 (1,115)	0,0212 (1,067)	0,0108 (0,501)	0,0108 (1,015)	0,2170
Decile 8	0,0101 (2,503**)	0,0116 (1,831*)	0,0114 (2,122**)	0,0119 (0,533)	-0,0111 (-1,742*)	0,0012 (1,892*)	-0,0121 (-1,844*)	-0,0105 (-1,203)	-0,0103 (-1,243)	-0,0125 (-1,052)	0,0091 (1,796*)	-0,0221 (-1,994**)	-0,0219 (-5,001***)	0,0204 (1,863*)	0,0111 (1,403)	0,0109 (0,082)	0,0106 (0,211)	0,1239
Decile 9	0,0112 (3,647***)	0,0112 (1,978**)	0,0118 (2,714***)	0,0120 (1,981**)	-0,0114 (-1,205)	0,0004 (1,774*)	-0,0110 (-1,999**)	-0,0104 (-1,735*)	-0,0107 (-1,023)	-0,0102 (-1,001)	0,0079 (1,662*)	-0,0186 (-2,383**)	-0,0111 (-4,214***)	-0,0112 (-1,671*)	0,0106 (1,648*)	0,0103 (1,661*)	0,0102 (1,385)	0,2915
Decile 10 (lowest volatility)	0,0108 (4,434***)	0,0110 (1,664*)	0,0116 (2,224**)	0,0113 (2,995***)	-0,0110 (-2,128**)	0,0006 (1,992**)	-0,0104 (-1,652*)	-0,0105 (-1,767*)	-0,0106 (-1,362)	-0,0101 (-1,240)	0,0021 (1,592)	-0,0135 (-2,125**)	-0,0109 (-1,744*)	-0,0102 (-1,819*)	0,0101 (1,931*)	0,0100 (1,681*)	0,0102 (0,066)	0,4512

Table A.13. Event effect on U.S. Industries - controlling for reversal effects

The table reports the results of the following regression:

$$r_{i,t} = \gamma_0 + \sum_{j=1}^{5}\gamma_{1,i} r_{i,t-j} + \sum_{k=1}^{4}\gamma_{2,k} WD_{k,t} + \gamma_3 Tax_t + \sum_{l=0}^{5}\gamma_{4,l}E_{l,t} + \epsilon_t$$

where $r_{i,t}$ is the rate of return of stock *i* on day *t* classified by industry of operation , γ_0 is the regression intercept, $r_{i,t-j}$ is the lagged dependent variable—the *j*th previous day rate of return, $WD_{k,t}$ with $k = 1, \dots, 4$ are dummy variables for the day of the week (Monday, Tuesday, Wednesday, and Thursday), Tax_t is a dummy variable for the first five days of the taxation year, and $E_{l,t}$ with $l = 0 \dots 5$, stands for possible event effect and reversal effect indicator. The events occurred during the 2014–2016 Ebola outbreak period (3-year period) and include a total number of 103 event days of the disease outbreak. From the total number of events, 52 took place in the WAC region, 31 in the U.S., and 20 in Europe. The first line reports the regression coefficients, while the second line reports the corresponding t-values (in brackets). One, two, and three asterisks indicate a significance level of 10%, 5%, and 1%, respectively. Industries have been selected by their contribution to U.S. GDP. Below presented, are the 12 largest by contribution industries according to S&P Dow Jones Industry Indexes.

Industry name	γ_0	R_{t-5}	R_{t-4}	R_{t-3}	R_{t-2}	R_{t-1}	Mon.	Tue.	Wed.	Thu.	Tax	$E_{t,0}$	$E_{t,1}$	$E_{t,2}$	$E_{t,3}$	$E_{t,4}$	$E_{t,5}$	R^2
Capital Markets	-0,0632 (-2,213**)	0,0126 (0,235)	0,0122 (1,043)	0,0183 (0,132)	0,0147 (1,041)	0,0151 (2,065**)	-0,0135 (-1,735*)	-0,0123 (-1,328)	-0,0122 (-1,021)	-0,0119 (-1,475)	0,0146 (1,254)	-0,0134 (-2,221**)	-0,0132 (-1,675*)	-0,0124 (-1,931*)	-0,0113 (-1,649*)	0,0102 (1,551)	0,0111 (1,423)	0,3609
Healthcare Equipment	0,0421 (1,873*)	0,0153 (1,661*)	0,0134 (1,024)	0,0155 (1,663*)	0,0124 (1,792*)	0,0117 (2,003**)	0,0132 (1,981**)	0,0126 (1,541)	0,0114 (0,204)	-0,0110 (-0,102)	0,0142 (1,321)	0,0250 (1,964**)	0,0243 (2,431**)	0,0206 (1,745*)	0,0156 (1,096)	0,0131 (0,143)	0,0155 (0,158)	0,5092
Crude Oil	-0,0722 (-1,541)	-0,0136 (-2,142**)	-0,0130 (-2,372**)	-0,0113 (-1,864*)	-0,0103 (-1,655*)	0,0031 (1,664*)	-0,0162 (-1,992**)	-0,0161 (-1,060)	-0,0148 (-1,321)	0,0121 (1,348)	0,0049 (1,685*)	-0,0171 (-1,982**)	-0,0170 (-1,721*)	-0,0142 (-1,828*)	-0,0133 (-1,126)	-0,0113 (-0,632)	-0,0122 (-1,857*)	0,2076
Industrials	-0,0491 (-2,645**)	-0,0191 (-1,697*)	-0,0172 (-0,251)	-0,0113 (-1,552)	-0,0116 (-0,011)	0,0125 (1,676*)	-0,0149 (-1,786*)	-0,0154 (-1,174)	-0,0132 (-1,447)	0,0225 (1,251)	0,0247 (0,085)	-0,0160 (-1,968**)	-0,0162 (-2,015**)	-0,0137 (-2,325**)	-0,0121 (-1,655*)	0,0113 (1,488)	0,0110 (1,024)	0,2649
Materials	-0,0103 (-1,842*)	-0,0138 (-1,952*)	-0,0136 (-1,652*)	-0,0123 (-2,164**)	-0,0126 (-1,999**)	-0,0015 (-2,003**)	-0,0118 (-1,679*)	-0,0113 (-1,088)	-0,0126 (-1,227)	0,0102 (1,344)	0,0145 (1,280)	-0,0155 (-1,994**)	-0,0152 (-1,824*)	-0,0144 (-1,662*)	-0,0126 (-1,667*)	-0,0112 (-1,269)	0,0105 (0,469)	0,3726
Information Technology	0,0534 (2,212**)	-0,0131 (-0,458)	0,0142 (1,447)	-0,0105 (-0,214)	-0,0103 (-1,962**)	-0,0113 (-1,654*)	-0,0147 (-1,688*)	-0,0151 (-0,522)	-0,0132 (-1,121)	0,0146 (1,526)	0,0216 (1,632)	-0,0165 (-2,302**)	-0,0148 (-1,656*)	-0,0122 (-2,352**)	-0,0111 (-1,647)	-0,0107 (-2,116**)	-0,0083 (-1,414)	0,2901
Utilities	-0,0213 (-1,555)	0,0132 (1,578)	0,0117 (1,831*)	-0,0124 (-1,662*)	-0,0123 (-1,112)	0,0114 (1,969**)	-0,0147 (-1,683*)	-0,0128 (-1,552)	-0,0196 (-1,123)	-0,0113 (-1,343)	-0,0203 (-1,336)	-0,0143 (-1,973**)	-0,0122 (-1,650*)	-0,0119 (-1,829*)	-0,0127 (-1,974**)	-0,0116 (-1,323)	0,0017 (1,126)	0,1298
Energy	-0,0612 (-1,966**)	-0,0124 (-1,753*)	-0,0138 (-1,412)	-0,0154 (-1,848*)	-0,0143 (-1,890*)	-0,0114 (-1,746*)	-0,0149 (-1,811*)	-0,0132 (-1,632)	-0,0137 (-1,191)	-0,0171 (-1,400)	-0,0107 (-1,485)	-0,0170 (-2,361**)	-0,0131 (-1,657*)	-0,0120 (-1,767*)	-0,0142 (-1,852*)	0,016 (1,655*)	0,0018 (0,344)	0,3117
Food & Beverage	0,0133 (2,213**)	-0,0111 (0,124)	-0,0133 (-1,246)	-0,0212 (-0,492)	-0,0174 (-1,732*)	0,0125 (1,935*)	0,0140 (1,701*)	0,0151 (1,130)	0,0136 (1,705)	0,0111 (0,556)	0,0218 (1,647*)	0,0172 (1,984**)	0,0161 (1,995**)	0,0159 (1,751*)	0,0111 (1,263)	0,0122 (1,947*)	-0,0010 (-1,558)	0,4457
Aviation	-0,0645 (-1,988**)	-0,0135 (-1,441)	0,0108 (1,501)	0,0138 (1,345)	0,0129 (0,346)	0,0133 (1,928*)	-0,0115 (-1,672*)	-0,0124 (-1,517)	0,0151 (1,112)	0,0161 (0,221)	-0,0263 (-1,974**)	-0,0334 (-1,963**)	-0,0238 (-1,997**)	-0,0029 (-1,654*)	0,0006 (1,635)	0,0032 (1,870*)	0,0044 (1,125)	0,3612
Pharma.	0,0312 (1,961**)	0,0129 (1,723*)	0,0127 (1,657*)	0,0125 (1,668*)	0,0115 (1,287)	0,0113 (1,923*)	0,0154 (2,335**)	0,0143 (1,535)	0,0129 (1,554)	0,0144 (1,238)	0,0162 (1,723*)	0,0197 (1,834*)	0,0152 (2,578***)	0,0156 (2,331**)	0,0127 (1,655)	0,0115 (0,678)	0,0118 (0,201)	0,3304
Biotech.	0,0461 (1,863*)	0,0126 (1,822*)	0,0225 (1,714*)	0,0135 (1,648*)	0,0217 (1,202)	0,0114 (2,162**)	0,0142 (1,961**)	0,0264 (1,556)	0,0172 (1,827*)	0,0032 (1,521)	0.0199 (2,002**)	0,0158 (2,252**)	0,0140 (1,967**)	0,0133 (2,887***)	0,0124 (1,647*)	0,0067 (0,542)	0,0059 (1,248)	0,2936

Table A.14. Intense media coverage effects on company securities - controlling for reversal effects
The table reports the results of the following regression:

$$r_{i,t} = \gamma_0 + \sum_{j=1}^{5} \gamma_{1,i} r_{i,t-j} + \sum_{k=1}^{4} \gamma_{2,k} WD_{k,t} + \gamma_3 Tax_t + \sum_{l=0}^{5} \gamma_{4,l} E_{l,t} + \epsilon_t$$

where $r_{i,t}$ is the rate of return of stock i on day t with exposure of its operations towards the U.S., the WAC region, Europe, or All regions, γ_0 is the regression intercept, $r_{i,t-j}$ is the lagged dependent variable—the jth previous day rate of return, $WD_{k,t}$ with $k = 1, \ldots, 4$ are dummy variables for the day of the week (Monday, Tuesday, Wednesday, and Thursday), Tax_t is a dummy variable for the first five days of the taxation year, and $E_{l,t}$ with $l = 0 \ldots 5$, stands for possible event effect and reversal effect indicator. The events occurred during the 2014–2016 Ebola outbreak period (3-year period) and include a total number of 103 event days of the disease outbreak. From the total number of events, 52 took place in the WAC region, 31 in the U.S., and 20 in Europe. Panel A depicts the regression results for the events and stocks with no intense media coverage (as in Panel A of Table 1) whereas Panel B depicts the regression results for the events and stocks intensely covered in the media. The first line reports the regression coefficients whereas the second line reports the corresponding t-values (in brackets). One, two, and three asterisks indicate a significance level of 10%, 5%, and 1%, respectively.

PANEL A: Regression results from events without intense media coverage

Exposure of the company to	γ_0	R_{t-5}	R_{t-4}	R_{t-3}	R_{t-2}	R_{t-1}	Mon.	Tue.	Wed.	Thu.	Tax	$E_{t,0}$	$E_{t,1}$	$E_{t,2}$	$E_{t,3}$	$E_{t,4}$	$E_{t,5}$	R^2
U.S. only	-0,0158 (-3,132***)	0,0220 (1,636)	-0,0144 (-0,900)	0,0245 (1,376)	-0,0120 (-1,791*)	0,0119 (3,242***)	-0,0321 (-1,980**)	-0,0108 (-1,298)	-0,0464 (-0,009)	-0,0541 (-1,295)	0.0305 (1,979**)	-0,0230 (-6,264***)	-0,0192 (-1,987**)	-0, 0155 (-1,632*)	-0,0112 (-2,851***)	-0,0102 (-0,541)	0,0120 (0,589)	0,4732
WAC region	-0,0413 (-2,761***)	0,0351 (1,616)	-0,0145 (-1,121)	0,0261 (1,132)	-0,0172 (-1,870*)	0,0183 (3,182***)	-0,0342 (-1,695*)	-0,0402 (-0,729)	-0,0801 (-0,127)	-0,0522 (-1,007)	0,0216 (1,673*)	-0,0278 (-2,129**)	-0,0201 (-1,750*)	-0,0163 (-1,987**)	-0,0125 (-1,812*)	-0,0113 (-1,407)	0,0135 (1,119)	0,5220
Europe	-0,0141 (-1,962**)	0,0240 (0,431)	-0,0123 (-1,012)	0,0205 (1,220)	-0,0112 (-1,668*)	0,0112 (1,939**)	-0,0281 (-1,684*)	-0,0102 (-1,106)	0,0359 (0,918)	-0,0516 (-1,227)	0,0250 (1,734*)	-0,0195 (-6,967***)	-0,0143 (-2,125**)	-0,0139 (-1,660*)	-0,0107 (-1,028)	-0,0052 (-0,542)	0,0025 (1,404)	0,6624
All	-0,0208 (-1,987**)	0,0314 (0,041)	-0,0128 (-0,310)	0,0226 (0,583)	-0,0148 (-4,312***)	0,0116 (3,581***)	-0,0312 (-2,231**)	-0,0254 (-1,296)	0,0454 (0,058)	-0,0470 (-1,326)	0,0288 (1,852*)	-0,0225 (-3,521***)	-0,0162 (-1,967**)	-0,0143 (-1,788*)	-0,0122 (-1,834*)	0,0111 (1,263)	0.0114 (0.955)	0.6032

PANEL B: Regression results from events with intense media coverage

Exposure of the company to	γ_0	R_{t-5}	R_{t-4}	R_{t-3}	R_{t-2}	R_{t-1}	Mon.	Tue.	Wed.	Thu.	Tax	$E_{t,0}$	$E_{t,1}$	$E_{t,2}$	$E_{t,3}$	$E_{t,4}$	$E_{t,5}$	R^2
U.S. only	-0,0266 (-3,210***)	0,0282 (1,521)	-0,0225 (-0,944)	0,0213 (1,241)	-0,0210 (-1,673*)	0,0219 (3,102***)	-0,0352 (-1,971**)	-0,0119 (-1,210)	-0,0452 (-1,019)	-0,0448 (-1,224)	0,0324 (1,988**)	-0,0336 (-5,2613***)	-0,0283 (-1,966**)	-0,0243 (-1,670*)	-0,0217 (-1,990**)	-0,0186 (-1,257)	0,0151 (1,185)	0,4256
WAC region	-0,0561 (-2,453**)	0,0389 (1,325)	-0,0349 (-1,527)	0,0336 (1,102)	-0,0310 (-1,913*)	0,0323 (1,901*)	-0,0331 (-1,674*)	-0,0200 (-1,224)	-0,0501 (-0,105)	-0,0542 (-1,014)	0,0231 (1,675*)	-0,0388 (-2,668***)	-0,0263 (-1,985**)	-0,0251 (-1,681*)	-0,0221 (-1,971**)	-0,0193 (-1,852*)	0,0164 (1,482)	0,4035
Europe	-0,0239 (-1,966**)	0,0261 (0,402)	-0,0223 (-0,012)	0,0312 (1,220)	-0,0212 (-1,647*)	0,0215 (1,948**)	-0,0242 (-1,723*)	-0,0112 (-1,125)	0,0327 (1,018)	-0,0436 (-1,205)	0,0258 (1,701*)	-0,0293 (-4,925***)	-0,0247 (-2,224**)	-0,0239 (-1,646*)	-0,0202 (-1,004)	-0,0142 (-1,511)	0,0125 (1,110)	0,3524
All	-0,0227 (-1,972**)	0,0331 (0,011)	-0,0221 (-0,641)	0,0306 (1,134)	-0,0201 (-4,011***)	0,0216 (3,532***)	-0,0332 (-2,320**)	-0,0244 (-0,198)	0,0472 (1,058)	-0,0431 (-1,186)	0,0291 (1,881*)	-0,0301 (-3,611***)	-0,0251 (-1,982**)	-0,0223 (-1,725*)	-0,0208 (-1,851*)	-0,0151 (-0,217)	0.0114 (1.053)	0.4931

Appendix B: Chapter 2

Table B.1 Definitions of the main variables

Variable	Variable Definitions
Abnormal Return (AR)	It is the difference between the actual rate of return of the stock considered and its ex-post expected rate of return over the whole length of the event window.
Cumulative average abnormal return (CAR)	It is the sum of the abnormal returns over the whole length of the event window.
Trump statements	Dummy variable equal to 1 if a firm is explicitly mentioned in Trump's statements and 0 otherwise.
Tweets	Events obtained from Trump's Twitter Archive.
News statements	Events obtained from the three largest by circulation U.S. newspapers.
Media excluding	Excludes all events in which media company is mentioned.
Negative	Events carrying negative linguistic tone.
Non-negative	Events carrying non-negative linguistic tone.
CEO Republican	Company's top management political orientation towards the Republican party.
CEO Democrat	Company's top management political orientation towards the Democratic party.
Connect	Dummy variable equal to 1 if a company is connected to Trump and 0 otherwise
No. of connections to Trump	Number of channels to which a company is connected to Trump.
Competitor conn. to Trump	Dummy variable equal to 1 if firm's competitor is connected to Trump and 0 otherwise.
Competitor tweeted	Dummy variable equal to 1 if firm's competitor is tweeted by Trump and 0 otherwise.
Altman z-score	It is the likelihood of company's bankruptcy.
Size	It is the log of total assets.
Profitability	It is the return on assets (ROA).
Leverage	It is the total debt to total capital.
Marginal tax rate	The amount of tax paid on an additional dollar of income.
International	Change of foreign assets as a % of total assets in the tweeting period.
CEO donation to Trump	Company's top management donnation to Trump but maybe also to Hillary Clinton
Abnormal trading volume (AV)	For each firm, it is the difference between the trading volume on a given day and mean trading volume over the whole length of the event window divided by the mean trading volume over the whole length of the event window.
Volatility	Stock price volatility is that level of volatility that will calculate a fair value that is equal to the current trading option price.

Table B.2 Trump's statements (event days)

The table reports detailed description of all 134 statements taken into consideration from June 2015 to June 2017 (449 trading days). All statements are sorted by "date", "source/type", "popularity"- likes and retweets, "tone", "description" and "companies exposed" in the statement. It is important to note that the statements are filtered to meet the non-overlapping properties as explained in Section 3. Of the total number of statements, 87 are categorized as statements of negative linguistic tone and 47 of non-negative linguistic tone. The Twitter statements are obtained from the official Trump Twitter archive (@realDonaldTrump) by filtering out all tweets in which Trump explicitly mentions a U.S. publicly listed company. The media statements are obtained from the LexisNexis news provider by browsing the three largest by circulation U.S. newspapers - The New York Times, Chicago Tribune and The Wall Street Journal. Key search term used in the LexisNexis news provider to yield at least a minimum of 95% relevance search score is: *Trump 2016 elections and U.S. companies*.

Date	Source/type	Tweet's likes	Tweet's retweets	Statements tone	Statement short description	Companies exposed in Trump's Statements
Jun 6, 2017 07:15:36 AM	Twitter	107984	26184	Negative	Sorry folks, but if I would have relied on the Fake News of CNN, NBC, ABC, CBS, washpost or nytimes, I would have had ZERO chance winning WH	CNN, NBC, ABC, CBS, Washington Post, NYT
May 4, 2017 07:28:39 AM	Twitter	29900	8316	Negative	Death spiral! 'Aetna will exit Obamacare markets in VA in 2018, citing expected losses on INDV plans this year'	Aetna
Apr 20, 2017 08:48:14 AM	Twitter	82232	19302	Negative	Failing @nytimes, which has been calling me wrong for two years, just got caught in a big lie concerning New England Patriots visit to W.H.	New York Times Co
Apr 1, 2017 10:59:36	Twitter	48953	11280	Negative	The failing @nytimes finally gets it - "In places where no insurance company offers plans, there will be no way for ObamaCare customers to...	New York Times Co
Mar 28, 2017 01:06 PM	News statements			Negative	Trump Touts NY Post Column Slamming NY Times	New York Times Co
Mar 28, 2017 06:16:44 AM	Twitter	57137	13257	Negative	The failing @NYTimes would do much better if they were honest!	New York Times Co
Mar 20, 2017 09:28 AM	News statements			Negative	Trump blasts 'fake news' CNN's polls	CNN-Time Warner
Mar 20, 2017 07:35:14 AM	Twitter	91700	18757	Negative	Just heard Fake News CNN is doing polls again despite the fact that their election polls were a WAY OFF disaster. Much higher ratings at Fox	CNN-Time Warner
Mar 15, 2017 07:27 AM	News statements			Negative	"Does anybody really believe that a reporter, who nobody ever heard of, 'went to his mailbox' and found my tax returns? @NBCNews FAKE NEWS!" Trump tweeted March 15, 2017	CBS Corp.
Mar 15, 2017 05:55:30 AM	Twitter	104115	26213	Negative	Does anybody really believe that a reporter, who nobody ever heard of, "went to his mailbox" and found my tax returns? @CBS News FAKE NEWS!	CBS Corp.
Mar 6, 2017 11:23 PM	News statements			Non-Negative	President Trump Praises Exxon Investment Announcement	Exxon Mobil
Mar 6, 2017	Twitter	100790	19672	Non-Negative	Thank you to @exxonmobil for your $20 billion	Exxon Mobil

08:50:49 PM					investment that is creating more than 45,000 manufacturing & construction jobs in the USA!	
Mar 6, 2017 03:10 PM	News statements			Non-Negative	ExxonMobil Plans Investments of $20 Billion to Expand Manufacturing in U.S. Gulf Region	Exxon Mobil
Feb 22/23, 2017	8-K				ExxonMobil Announces 2016 Reserves	Exxon Mobil
Feb 24, 2017 10:19 PM	News statements			Negative	Trump’s New Tweet: Fake News Media ‘Knowingly Doesn’t Tell the Truth’ and It’s a ‘Danger to Our Country’	New York Times Co, CNN-Time Warner
Feb 24, 2017 08:09:18 PM	Twitter	110563	26720	Negative	FAKE NEWS media knowingly doesn't tell the truth. A great danger to our country. The failing @nytimes has become a joke. Likewise @CNN. Sad!	New York Times Co, CNN-Time Warner
Feb 23, 2017 03:53:45 PM	Twitter	57031	10706	Non-Negative	'S&P 500 Edges Higher After Trump Renews Jobs Pledge'	Nvidia, L Brands, Edwards Lifesciences
Feb 23, 2017 3:08 PM	News statements			Non-Negative	US STOCKS-S&P 500 edges higher after Trump renews jobs pledge	Nvidia, L Brands, Edwards Lifesciences
Feb 22, 2017	8-K				L BRANDS REPORTS FOURTH QUARTER AND FULL-YEAR 2016 EARNINGS	L Brands
Feb 9, 2017	8-K				NVIDIA Announces Financial Results for Fourth Quarter and Fiscal 2017	Nvidia
Feb 17, 2017 04:57 PM	News statements			Negative	Trump tweets 'fake news media' is 'the enemy of the American people'	New York Times Co, CNN-Time Warner, CBS Corp., ABC-Disney
Feb 17, 2017 02:48:22 PM	Twitter	162791	51326	Negative	The FAKE NEWS media (failing @nytimes, @CBS News, @ABC, @CBS, @CNN) is not my enemy, it is the enemy of the American People!	New York Times Co, CNN-Time Warner, CBS Corp., ABC-Disney
Feb 15, 2017	8-K			Non-Negative	CBS Corp. Annual report	CBS Corp.
Feb 17, 2017 06:38:20 AM	Twitter	100591	14556	Non-Negative	Going to Charleston, South Carolina, in order to spend time with Boeing and talk jobs! Look forward to it.	Boeing
Feb 16, 2017 07:15 AM	News statements			Negative	Trump: Spotlight is on 'low-life leakers'	New York Times Co
Feb 16, 2017 06:58:43 AM	Twitter	91146	17359	Negative	Leaking, and even illegal classified leaking, has been a big problem in Washington for years. Failing @nytimes (and others) must apologize!	New York Times Co
Feb 15, 2017 05:24 PM	News statements			Non-Negative	Aetna CEO: Obamacare in 'Death Spiral'	Aetna, CBS Corp.
Feb 15, 2017 02:34:05 PM	Twitter	59626	14791	Non-Negative	Aetna CEO: Obamacare in 'Death Spiral' #RepealAndReplace	Aetna
Feb 15, 2017 12:17 PM	News statements			Negative	Trump: Intelligence community giving out classified information to press ‘like candy’	New York Times Co, Washington Post
Feb 15, 2017	Twitter	81702	21450	Negative	Information is being illegally given to the failing	New York Times Co, Washington Post

07:19:18 AM					@nytimes & @washingtonpost by the intelligence community (NSA and FBI?) Just like Russia	
Feb 15, 2017 06:57 AM	News statements			Negative	Trump: CNN, CBS reporting 'conspiracy theories' and 'blind hatred'	CNN-Time Warner, CBS Corp.
Feb 15, 2017 06:40:32 AM	Twitter	106193	26272	Negative	The fake news media is going crazy with their conspiracy theories and blind hatred. @CBS & @CNN are unwatchable. @foxandfriends is great!	CNN-Time Warner, CBS Corp.
Feb 13, 2017 07:24 AM	News statements			Non-Negative	Trump Border Tax: Profitable Pickups May Be in Cross Hairs	Ford, General Electric, Toyota Motor Corp, Fiat Chrysler, General Motors
Feb 10, 2017 09:19 AM	News statements			Negative	Donald Trump Calls *New York Times* 'Fake News' For Perfectly Accurate Reporting	New York Times Co
Feb 10, 2017 08:35:50 AM	Twitter	7	8	Negative	The failing @nytimes does major FAKE NEWS China story saying "Mr.Xi has not spoken to Mr. Trump since Nov.14." We spoke at length yesterday!	New York Times Co
Feb 9, 2017 10:25 AM	News statements			Non-Negative	Trump on 'Phenomenal' Tax Plan sends message to the big market players	Brightcove, Inc, Citrix Systems, Harmonic Inc, Archer-Daniels-Midland Co, Trip Advisor, Rocket Fuel, Bank of America, Cavium, WPP
Feb 9, 2017	8-K			Non-Negative	Intel Corporation Report	Intel
Feb 8, 2017 02:22:33 PM	Twitter	78	36	Non-Negative	Thank you Brian Krzanich, CEO of @Intel. A great investment ($7 BILLION) in American INNOVATION and JOBS! #AmericaFirst	Intel
Feb 8, 2017 01:04 PM	News statements			Non-Negative	Intel to invest $7 billion in factory in Arizona, employ 3,000	Intel
Feb 9, 2017 07:31 AM	News statements			Non-Negative	Nordstrom Says It Told Ivanka Trump Last Month It Would Stop Carrying Her Lin	Nordstrom Inc
Feb 8, 2017 10:56 AM	News statements			Negative	Trump slams Nordstrom for dropping Ivanka's fashion line	Nordstrom Inc
Feb 8, 2017 10:51:01 AM	Twitter	0	0	Negative	My daughter Ivanka has been treated so unfairly by @Nordstrom. She is a great person -- always pushing me to do the right thing! Terrible!	Nordstrom Inc
Feb 6, 2017 10:10 PM	News statements			Negative	Trump Slams *NYT* Again Minutes After Reporter Defends White House Piece on CNN	New York Times Co
Feb 6, 2017 09:33:55 PM	Twitter	0	2	Negative	The failing @nytimes was forced to apologize to its subscribers for the poor reporting it did on my election win. Now they are worse!	New York Times Co
Feb 6, 2017 06:11 PM	News statements			Negative	Sean Spicer: *NY Times* Owes Trump Apology for Report 'Riddled with Inaccuracies'	New York Times Co

Feb 6, 2017 11:47 AM	News statements			Negative	Trump: New York Times writing 'total fiction,' 'making up stories' about administration	New York Times Co
Feb 6, 2017 11:32:24 AM	Twitter	462	169	Negative	The failing @nytimes writes total fiction concerning me. They have gotten it wrong for two years, and now are making up stories & sources!	New York Times Co
Feb 6, 2017 08:01 AM	News statements			Negative	Trump claims that any negative polls are "fake news"	CBS Corp., CNN-Time Warner, ABC-Disney
Feb 6, 2017 07:01:53 AM	Twitter	3	5	Negative	Any negative polls are fake news, just like the CNN, ABC, CBS polls in the election. Sorry, people want border security and extreme vetting.	CBS Corp., CNN-Time Warner, ABC-Disney
Feb 3, 2017 12:38 PM	News statements			Non-Negative	“Good jobs are coming back to U.S, health care and tax bills are being crafted NOW!” - Trump Moves to Roll Back Obama-Era Financial Regulations Too	Apple, Facebook, General Electric, Eli Lilly, Ford Motor, Google, Nabisco, Microsoft, Castlight Health, Celgene Corp, Amgen Inc, Exxon Mobil, Boeing, Macy’s, Comcast
Feb 1, 2017 01:00 AM	News statements			Non-Negative	Trump Says: No More Bad News on Drug Pricing!	Castlight Health, Bristol-Myers Squibb, Eli Lilly, Allergan, Pfizer, Merck, Amgen
Jan 30, 2017 07:37 AM	News statements			Negative	Trump says Delta, protesters caused airport problems	Delta Air Lines Inc
Jan 30, 2017 07:16:30 AM	Twitter	86	62	Negative	Only 109 people out of 325,000 were detained and held for questioning. Big problems at airports were caused by Delta computer outage	Delta Air Lines Inc
Jan 29, 2017 09:02 AM	News statements			Negative	Trump: 'Somebody with aptitude and conviction should buy' the New York Times	New York Times Co
Jan 29, 2017 08:00:32 AM	Twitter	56	41	Negative	Somebody with aptitude and conviction should buy the FAKE NEWS and failing @nytimes and either run it correctly or let it fold with dignity	New York Times Co.
Jan 28, 2017 08:45 AM	News statements			Negative	Trump slams New York Times, Washington Post in tweets	Washington Post, New York Times Co
Jan 28, 2017 08:08:42 AM	Twitter	22	19	Negative	The coverage about me in the @nytimes and the @washingtonpost gas been so false and angry that the times actually apologized to its…	Washington Post, New York Times Co.
Jan 28, 2017 12:03 PM	News statements			Non-Negative	Trump's Travel Ban: Companies and Executives Vs. Trump on Public Speak Out	Facebook, Tesla, Google, Microsoft, Wayfair, Amazon.com Inc, Netflix Inc, Coca-Cola
Jan 25, 2017 07:54 AM	News statements			Non-Negative - FoxNews/ Negative-CNN	CNN fires back at Trump on inauguration ratings winner	Fox News, CNN-Time Warner
Jan 25, 2017 03:16:19 AM	Twitter	30926	7142	Non-Negative - FoxNews/ Negative-CNN	Congratulations to @FoxNews for being number one in inauguration ratings. They were many times higher than FAKE NEWS @CNN - public	Fox News, CNN-Time Warner

					is smart!	
Jan 24, 2017 05:46:57 PM	Twitter	37754	7748	Non-Negative	Great meeting with Ford CEO Mark Fields and General Motors CEO Mary Barra at the @WhiteHouse today.	Ford, General Motors
Jan 24, 2017 03:03 PM	News statements			Non-Negative	Detroit at the White House: Trump meets with Big Three auto CEOs	Ford, General Motors
Jan 23, 2017 04:00 PM	News statements			Negative	Trump on a 'Very Major' Border Tax Points to Specificities	Lockheed Martin Corp, Boeing
Jan 18, 2017 07:34:09 AM	Twitter	25325	6398	Negative- CBS / Non-Negative F, GM, Lockheed	Totally biased @CBS News went out of its way to say that the big announcement from Ford, G.M., Lockheed & others that jobs are coming back...	CBS Corp., Ford, General Motors, Lockheed Martin
Jan 18, 2017 07:20 AM	News statements			Non-Negative	Fact Checking Donald Trump's Job Creation Claims	CBS Corp., Ford, General Motors, Lockheed Martin
Jan 17, 2017 10:55:38 PM	Twitter	21740	5181	Non-Negative	Thank you to General Motors and Walmart for starting the big jobs push back into the U.S.!	General Motors, Walmart
Jan 17, 2017 11:05 PM	News statements			Non-Negative	General Motors falls in line, joins Ford, Fiat Chrysler in touting new U.S. investments after Trump tweets-updated after tweet	General Motors, Walmart
Jan 10, 2017	8-K			Non-Negative	GM Expects Earnings Growth Again in 2017; Increases Stock Repurchase Program	General Motors
Jan 15, 2017 06:06 PM	News statements			Negative	Trump Attacks *Saturday Night Live*, Calling It the 'Worst of NBC' and 'Really Bad Television'	CBS Corp.
Jan 15, 2017 03:46:33 PM	Twitter	49318	12107	Negative	@CBS News is bad but Saturday Night Live is the worst of CBS. Not funny, cast is terrible, always a complete hit job. Really bad television!will only get higher.	CBS Corp.
Jan 11, 2017 12:46 PM	News statements			Negative	Big Pharma Lost $24.6 Billion in 20 Minutes During Donald Trump's Press Conference	Castlight Health, Bristol-Myers Squibb, Eli Lilly, Allergan, Pfizer, Merck, Amgen
Jan 9, 2017 09:27 AM	News statements			Non-Negative	Fiat to Invest $1 Billion in Michigan, Ohio Plants; Create 2,000 Jobs	Fiat Chrysler
Jan 9, 2017 09:14:10 AM	Twitter	29661	8077	Non-Negative	It's finally happening - Fiat Chrysler just announced plans to invest $1BILLION in Michigan and Ohio plants, adding 2000 jobs. This after...	Fiat Chrysler
Jan 8, 2017 09:54 PM	News statements			Non-Negative	Fiat Chrysler Announces Plans to Invest $1 Billion in the U.S.	Fiat Chrysler
Jan 4, 2017 10:47 AM	News statements			Non-Negative	Ford cancels Mexico plant. Will create 700 U.S. jobs in 'vote of confidence' in Trump	Ford
Jan 4, 2017 08:19:09 AM	Twitter	39855	10116	Non-Negative	Thank you to Ford for scrapping a new plant in Mexico and creating 700 new jobs in the U.S. This is just the beginning - much more to follow	Ford
Jan 3, 2017	News			Negative	Trump Uses His Pointer. Ford Cancels Plans for	Ford

05:43 PM	statements				Mexico Plant Even Before He Takes Office	
Jan 3, 2017 07:59 AM	News statements			Negative	Trump threatens 'big border tax' on GM over Chevy Cruze production	General Motors
Jan 3, 2017 07:30:05 AM	Twitter	975	317	Negative	General Motors is sending Mexican made model of Chevy Cruze to U.S. car dealers-tax free across border. Make in U.S.A. or pay big border tax!	General Motors
Dec 23, 2016 11:43 AM	News statements			Negative	Trump's Health Choice Traded Medical Stocks in Congress	Johnson & Johnson Allergan, Pfizer, Merck
Dec 22, 2016 11:57 PM	News statements			Non-Negative	Trump Says He Asked Boeing to Price a Competitor to Lockheed's F-35	Lockheed Martin Corp, Boeing
Dec 22, 2016 03:26:05 PM	Twitter	62693	14954	Negative-LM / Non-Negative - Boeing	Based on the tremendous cost and cost overruns of the Lockheed Martin F-35, I have asked Boeing to price-out a comparable F-18 Super Hornet!	Lockheed Martin Corp, Boeing
Dec 19, 2016 07:51 AM	News statements			Non-Negative	Lockheed Bows To Trump, Agrees To Cut F-35 Prices	Lockheed Martin Corp,
Dec 15, 2016 08:09:14 AM	Twitter	57035	10718	Non-Negative	Thank you to Time Magazine and Financial Times for naming me "Person of the Year" - a great honor!	Time, FT
Dec 7, 2016 02:16 PM	News statements			Non-Negative	TIME Person of the Year for 2016 is President-elect Donald Trump	Time
Dec 13, 2016 06:43:38 AM	Twitter	76990	23120	Non-Negative	I have chosen one of the truly great business leaders of the world, Rex Tillerson, Chairman and CEO of ExxonMobil, to be Secretary of State.	Exxon Mobil Corp
Dec 12, 2016 09:37 PM	News statements			Non-Negative	President-elect Trump selects Exxon Mobil CEO Tillerson as Sec. of State	Exxon Mobil Corp
Dec 6, 2016 08:56 PM	News statements			Negative	Trump on Boeing's Air Force One contract: 'Cancel order!'	Boeing
Dec 6, 2016 08:52:35 AM	Twitter	141634	42984	Negative	Boeing is building a brand new 747 Air Force One for future presidents, but costs are out of control, more than $4 billion. Cancel order!	Boeing
Dec 2, 2016 07:36 PM	News statements			Non-Negative	Donald Trump on Top Pharma Companies	Allergan, Pfizer, Merck, Aetna
Nov 25, 2016 08:20 PM	News statements			Negative	Trump Leans on Carrier and Ford to Keep 2,000 U.S. Jobs From Moving to Mexico	Carrier, Ford
Dec 1, 2016	8-K				Ford Total U.S. Sales Up 5 Percent in November, Retail Up 10 Percent; F-Series, SUVs and Lincoln Vehicles Drive Gains	Ford
Nov 18, 2016 12:45 PM	News statements			Non-Negative	Ford says Trump influenced its decision to keep a Lincoln production line in Kentucky	Ford
Nov 17, 2016	Twitter	117953	29271	Non-Negative	I worked hard with Bill Ford to keep the Lincoln	Ford

07:15:28 PM					plant in Kentucky. I owed it to the great State of Kentucky for their confidence in me!	
Nov 17, 2016 07:01:52 PM	Twitter	166484	49187	Non-Negative	Just got a call from my friend Bill Ford, Chairman of Ford, who advised me that he will be keeping the Lincoln plant in Kentucky - no Mexico	Ford
Nov 17, 2016	8-K			Non-Negative	Ford Motor Com. Report	Ford
Nov 15, 2016 06:14 PM	News statements			Non-Negative	Ford CEO Wary of Trump's Talk About Tariffs and NAFTA	Ford
Nov 12, 2016 04:28 PM	News statements			Negative	"The Black List" – The 127 Companies Trump Has Bashed	*All companies with negative exposure as stated in the table below*
Oct 30, 2016 11:53 AM	News statements			Negative	Donald Trump baselessly claims Google, Twitter, and Facebook are suppressing Clinton email news	Twitter, Google, Facebook
Oct 30, 2016 09:26:30 AM	Twitter	72013	35433	Negative	Wow, Twitter, Google and Facebook are burying the FBI criminal investigation of Clinton. Very dishonest media!	Twitter, Google, Facebook
Oct 10, 2016 04:26 PM	News statements			Negative	CNN pushes back on Trump's claim it 'rigged' focus group	CNN-Time Warner
Oct 10, 2016 02:31:04 PM	Twitter	69788	28837	Negative	Wow, @CNN got caught fixing their "focus group" in order to make Crooked Hillary look better. Really pathetic and totally dishonest!	CNN-Time Warner
Sep 17, 2016 09:42 AM	News statements			Negative	Trump: CNN panelists 'mostly losers in life'	CNN-Time Warner
Sep 17, 2016 08:13:43 AM	Twitter	39146	12708	Negative	CNN just doesn't get it, and that's why their ratings are so low - and getting worse. Boring anti-Trump panelists, mostly losers in life	CNN-Time Warner
Sep 9, 2016 11:44 AM	News statements			Negative	Donald Trump blasts CNN's Jeff Zucker over biographical documentary	CNN-Time Warner
Sep 8, 2016 09:10:49 PM	Twitter	26229	8075	Negative	The documentary of me that @CNN just aired is a total waste of time. I don't even know many of the people who spoke about me. A joke!	CNN-Time Warner
Aug 19, 2016 07:43:37 AM	Twitter	20652	5721	Negative	The reporting at the failing @nytimes gets worse and worse by the day. Fortunately, it is a dying newspaper	New York Times Co
Aug 1, 2016 10:07 AM	News statements			Negative	Exclusively for the Press: "Vast numbers of jobs in Pennsylvania and U.S. in general have moved to Mexico and other countries, it's enough!"	IBM, Cisco, Google, Microsoft, Advance Auto Parts, V F Corp, AT&T Inc, Thermo Fisher Scientific, Caleres, Wayfair, Dillard's, Albemarle Corporation, Salesforce, Cemex, Glu Mobile, Square, Sociedad Quimica y Minera, Nike, Brocade Communications Systems

Jul 24, 2016 08:22 PM	News statements			Negative/ Non-Negative	Trump Goes on Total Tweetstorm Against ‘Biased Media’, DNC, and ‘Crooked Hillary’	Fox News, CNN-Time Warner
Jul 24, 2016 03:45:31 PM	Twitter	30900	9400	CNN-Negative/Fox-Non-Negative	The @CNN panels are so one sided, almost all against Trump. @FoxNews is so much better and the ratings are much higher. Don't watch CNN!	Fox News, CNN-Time Warner
Jul 18, 2016 05:00 PM	News statements			Negative	Trump After Never-Trumpers Denied Vote: 'VAST MAJORITY' Want Me!	CNN-Time Warner
Jul 18, 2016 01:48:00 PM	Twitter	29909	8285	Negative	CNN is the worst. They go to their dumb, one-sided panels when a podium speaker is for Trump! VAST MAJORITY want: Make America Great Again!	CNN-Time Warner
Jul 12, 2016 01:14 PM	News statements			Negative	Sanders, Trump in Twitter fight over Clinton endorsement	Goldman Sachs
Jul 12, 2016 10:01:51 PM	Twitter	53157	36168	Negative	Bernie Sanders endorsing Crooked Hillary Clinton is like Occupy Wall Street endorsing Goldman Sachs.	Goldman Sachs
Jul 12, 2016 08:00 PM	News statements			Negative	Trump Bashes Bernie: 'Like Occupy Wall Street Endorsing Goldman Sachs'	Goldman Sachs
Jul 6, 2016 08:34 PM	News statements			Negative	Donald Trump Drags ‘Frozen’ Into Star of David Controversy	Disney
Jul 6, 2016 04:22:20 PM	Twitter	61853	25762	Negative	Where is the outrage for this Disney book? Is this the 'Star of David' also? Dishonest media! #Frozen https://t.co/4LJBpSm8xa	Disney
Jun 26, 2016 12:41 PM	News statements			Negative	Two New Polls Show Hillary Still Comfortably Leading Trump	Washington Post, ABC-Disney
Jun 26, 2016 04:13:25 PM	Twitter	15087	5143	Negative	The "dirty" poll done by @ABC @washingtonpost is a disgrace. Even they admit that many more Democrats were polled. Other polls were good	Washington Post, ABC-Disney
Jun 26, 2016 11:21:15 AM	Twitter	14059	4622	Negative	The @ABC poll sample is heavy on Democrats. Very dishonest - why would they do that? Other polls good!	ABC-Disney
Jun 23, 2016 03:59:35 PM	News statements			Negative	Trump slams CNN after network hires ex-aide Lewandowski	CNN-Time Warner
Jun 23, 2016 02:34:35 PM	Twitter	13021	6169	Negative	CNN, which is totally biased in favor of Clinton, should apologize. They knew they were wrong	CNN-Time Warner
May 20, 2016 11:11:21 AM	Twitter	12251	3726	Negative	Failing @NYTimes will always take a good story about me and make it bad. Every article is unfair and biased. Very sad!	New York Times Co.
May 15, 2016 11:33 PM	News statements			Negative	Trump: Rubio Not Being Considered for VP	Washington Post
May 15, 2016 06:25:54 PM	Twitter	15747	6030	Negative	The @washingtonpost report on potential VP candidates is wrong. Marco Rubio and most	Washington Post

					others mentioned are NOT under consideration.	
May 15, 2016 09:53 AM	News statements			Negative	Donald Trump fires back over "lame hit piece" on women	New York Times Co
May 15, 2016 05:55:39 AM	Twitter	12849	3855	Negative	The failing @nytimes wrote yet another hit piece on me. All are impressed with how nicely I have treated women, they found nothing. A joke!	New York Times Co
May 4, 2016 09:32 AM	News statements			Negative	Trump Declares War on Mexico. Ford, GM and GE Uncovered	Ford, General Motors, General Electric
Apr 11, 2016 04:53 AM	News statements			Negative	Trump chucked a tanty at Boston globe’s worthless satirical front page	New York Times Co
Apr 10, 2016 08:40:23 AM	Twitter	14446	5211	Negative	The @nytimes purposely covers me so inaccurately. I want other nations to pay the U.S. for our defense of them. We are the suckers-no more!	New York Times Co
Apr 2, 2016 01:31:12 PM	Twitter	13734	4794	Negative	FoxNews should be ashamed for allowing experts to explain how to make a nuclear attack!	Fox News
Feb 19, 2016 06:24 PM	News statements			Negative	From Oreo to HBO: All the companies and countries Donald Trump publicly has boycotted today	Oreo-Nabisco, HBO
Jul 11, 2015 06:46:36 AM	Twitter	1132	649	Negative	Boycott @Macys and @CW Inc. MAKE AMERICA GREAT AGAIN!	Macy’s, CW Inc.
Jun 26, 2015 03:50 PM	News statements			Negative	Donald Trump is locked in all-out war with one of the US' largest TV network	CNN-Time Warner
Jun 26, 2015 09:07:44 AM	Twitter	1191	716	Negative	Anyone who wants strong borders and good trade deals for the US should boycott @CNN-Time Warner.	CNN-Time Warner.

Table B.3 Companies exposed in Trump's statements

The table lists U.S. publicly listed companies on NYSE and Nasdaq which are regarded as having exposure to Trump's public statements. The total number of companies is 111 and it is obtained by the selection procedure which goes as follows. First, I browse the media (Trump Twitter archive and U.S. Newspapers) to filter out all the companies explicitly mentioned in Trump's statements. Second, I select the companies by status – I am interested in active and publicly listed companies. Third, I further select the companies that have a domicile in the U.S. And fourth, I set up the period of operation of the companies of interest - June 2015 to June 2017. The data is obtained from Bloomberg's and LexisNexis databases.

Name of the Company	Ticker	Exchange	SIC code	CIK (SEC filings number)	Cusip
21st Century Fox	FOXA	NASDAQ	2711	1054263	90130A10
AbbVie	ABBV	NYSE	2834	1551152	00287Y10
Accenture plc	ACN	NYSE	7389	1467373	G1151C10
Adobe Systems	ADBE	NASDAQ	7372	796343	00724F10
Advance Auto Parts	AAP	NYSE	5531	1158449	00751Y10
Aetna	AET	NYSE	6324	1013761	00817Y10
Albemarle Corporation	ALB	NYSE	2821	915913	01265310
Allergan	AGN	NYSE	2834	850693	G0177J108
Amazon Com Inc	AMZN	NASDAQ	5961	1018724	02313510
American Airlines Group	AAL	NASDAQ	4512	6201	02376R10
Amgen Inc	AMGN	NASDAQ	2836	318154	03116210
Apple	AAPL	NYSE	3571	320193	03783310
Archer-Daniels-Midland	ADM	NYSE	2070	7084	03948310
AT&T Inc	T	NYSE	4813	732717	00206R102
Atlassian	TEAM	NASDAQ	7372	1650372	G0624210
Autodesk, Inc	ADSK	NASDAQ	7372	769397	05276910
Bank of America	BAC	NYSE	6021	70858	06050510
BlackRock	BLK	NYSE	6211	1364742	09247X10
Boeing	BA	NYSE	3721	12927	09702310
Box	BOX	NYSE	7372	1372612	10316T10
Brightcove, Inc	BCOV	NYSE	7372	1535379	10921T10
Bristol-Myers Squibb	BMY	NYSE	2834	14272	11012210
Broadcom	AVGO	NASDAQ	3674	1054374	Y09827109
Brocade Communications Systems	BRCD	NASDAQ	3576	1009626	11162130
Caleres	CAL	NYSE	3140	14707	12950010

Castlight Health	CSLT	NYSE	7374	1433714	14862Q10
Caterpillar Inc.	CAT	NYSE	3531	18230	14912310
Cavium	CAVM	NASDAQ	3674	1175609	14964U10
CBS Corporation	CBS	NYSE	4833	0000813828	12485720
Celgene Corp	CELG	NASDAQ	2834	816284	15102010
Cemex	CX	NYSE	3241	1118420	15129088
Cisco	CSCO	NASDAQ	3576	858877	17275R10
Citrix Systems	CTXS	NASDAQ	7372	877890	17737610
Coca-Cola	KO	NYSE	2080	21344	19121610
Comcast	CMCSA	NASDAQ	4813	1166387	20030N10
ConocoPhillips	COP	NYSE	2911	1163165	20825C10
Curtiss Wright Corp.	CW	NYSE	4833	1640579	23156110
Delta Air Lines Inc	DAL	NYSE	4512	27904	24736170
Dillard's	DDS	NYSE	5311	28917	25406710
Disney	DIS	NYSE	7812	29082	25468710
Dun and Bradstreet	DNB	NYSE	6189	884099	26483E10
Eaton Corporation	ETN	NYSE	3590	31277	G2918310
eBay Inc.	EBAY	NASDAQ	7389	1065088	27864210
Edwards Lifesciences	EW	NYSE	3842	0001099800	28176E10
Eli Lilly	LLY	NYSE	2834	59478	53245710
Etsy	ETSY	NASDAQ	7389	0001370637	29786A10
Expedia	EXPE	NASDAQ	4700	1095357	30212P30
Exxon Mobil Corp	XOM	NYSE	2911	34088	30231G10
Facebook	FB	NASDAQ	7370	1326801	30303M10
Fedex	FDX	NYSE	4513	1048911	31428X10
Fiat Chrysler	FCAU	NYSE	3711	1605484	N3173810
FMC Corporation	FMC	NYSE	2800	37785	30249130
Ford Motor	F	NYSE	3711	37996	34537086
General Electric	GE	NYSE	3600	40545	36960410
General Mills	GIS	NYSE	2040	40704	37033410
General Motors	GM	NYSE	3711	1467858	37045V10

Gilead Sciences inc	GILD	NASDAQ	2836	882095	37555810
Glu Mobile	GLUU	NASDAQ	7371	1366246	37989010
Goldman Sachs	GS	NYSE	6211	1098457	38141G10
Google	GOOGL	NASDAQ	7370	1288776	02079K305
GoPro, Inc	GPRO	NASDAQ	3861	0001500435	38268T10
Harmonic Inc.	HLIT	NASDAQ	3663	851310	41316010
HBO-Time Warner	TWX	NYSE	7812	893657	88731730
Hershey	HSY	NYSE	2060	47111	42786610
Hewlett-Packard Company	HPQ	NYSE	3570	1645590	40434L105
HSN, Inc	HSNI	NASDAQ	5940	1434729	404303109
IBM	IBM	NYSE	3570	51143	45920010
Intel	INTC	NASDAQ	3674	50863	45814010
Johnson & Johnson	JNJ	NYSE	2834	200406	47816010
JPMorgan Chase & Co	JPM	NYSE	6021	19617	46625H10
L Brands	LB	NYSE	5621	0000701985	50179710
Lockheed Martin Corp	LMT	NYSE	3760	936468	53983010
Macy’s	M	NYSE	5311	794367	55616P10
Merck	MRK	NYSE	2834	310158	58933Y10
Microsoft	MSFT	NASDAQ	7372	789019	59491810
Nabisco-Mondelēz International	MDLZ	NASDAQ	2000	69526	60920710
Netflix, Inc.	NFLX	NASDAQ	7841	1065280	64110L10
Netgear, Inc	NTGR	NASDAQ	3661	0001122904	64111Q10
New Relic	NEWR	NYSE	7372	1448056	64829B10
New York Times Co	NYT	NYSE	2711	71691	65011110
Nike	NKE	NYSE	3021	320187	65410610
Nordstrom	JWN	NYSE	5651	72333	65566410
Novartis AG	NVS	NYSE	2834	1114448	66987V10
Nvidia Corporation	NVDA	NASDAQ	3674	1045810	67066G10
Oracle	ORCL	NYSE	7372	1341439	68389X10
Patterson Companies	PDCO	NASDAQ	5047	891024	70339510
Pfizer	PFE	NYSE	2834	78003	71708110

Rocket Fuel	FUEL	NASDAQ	7370	1477200	77311110
RPX Corporation	RPXC	NASDAQ	6794	1509432	74972G10
Salesforce	CRM	NYSE	7372	1108524	79466L30
Shutterstock	SSTK	NYSE	7374	1549346	82569010
Sociedad Quimica y Minera	SQM	NYSE	4899	1415332	83363510
Square	SQ	NYSE	7372	1512673	85223410
Starbucks Corp	SBUX	NASDAQ	5810	829224	85524410
T.J. Maxx	TJX	NYSE	5651	814445	87254010
Tesla Inc	TSLA	NASDAQ	3711	1318605	88160R10
Thermo Fisher Scientific	TMO	NYSE	3829	97745	88355610
Time Inc.	TIME	NYSE	2721	1591517	88722810
Time Warner	TWX	NYSE	7812	893657	88731730
Toyota Motor Corp	TM	NYSE	3711	1094517	89233130
TripAdvisor	TRIP	NASDAQ	7370	0001526520	89694520
United Continental Holdings	UAL	NYSE	4512	100517	91004710
United Technologies Corp	UTX	NYSE	3724	101829	91301710
V F Corp	VFC	NYSE	2320	103379	91820410
Wal-Mart	WMT	NYSE	5331	104169	93114210
Washington Post-Graham Holdings Co	GHC	NYSE	8200	104889	38463710
Wayfair	W	NYSE	5961	1616707	94419L10
Workday, Inc	WDAY	NYSE	7374	1327811	98138H10
WPP Group PLC	WPPGY	NASDAQ	7311	806968	92937A10
Yelp	YELP	NYSE	7200	1345016	98581710
Zynga	ZNGA	NASDAQ	7374	1439404	98986T10

Table B.4 Companies classified by exposure to Trump statements' linguistic tone

The table lists the U.S. publicly listed companies on NYSE and Nasdaq which are regarded as having exposure to Trump's public statements. The companies are categorized according to the linguistic tone (negative and non-negative) by which they are exposed in the specific statement. It is important to note that some companies appear in more than one group. The total number of companies is obtained by the selection procedure which goes as follows. First, I browse the media (Trump Twitter archive and U.S. Newspapers) to filter out all the companies explicitly mentioned in Trump's statements. Second, I select the companies by status – I am interested in active and publicly listed companies. Third, I further select the companies that have a domicile in the U.S. And fourth, I set up the period of operation of the companies of interest - June 2015 to June 2017. The data is obtained from Bloomberg's LexisNexis databases.

Companies negatively exposed			**Companies non-negatively exposed**	
AbbVie	Dun and Bradstreet	New York Times Co	Aetna	Lockheed Martin
ABC-Disney	Eaton Corporation	Nike	Allergan	Macy's
Accenture plc	Ebay	Nordstrom Inc	Alphabet	Merck
Adobe Systems	Eli Lilly	Novartis	Amazon.com	Microsoft
Advance Auto Parts	Etsy	Oracle	Amgen	Nabisco
Albemarle Corp.	Etsy	Oreo-Nabisco	Apple	Netflix, Inc
Allergan	Expedia	Patterson Comp.	Archer-Daniels-Mid.	Nvidia Corp
American Airlines	Facebook	Pfizer	Bank of America	Pfizer
Amgen	Fedex	RPX Corp.	Boeing	Rocket Fuel
Apple	FMC Corporation	Salesforce	Brightcove Inc	Tesla
AT&T Inc	Ford	Shutterstock	Bristol-Myers Sq.	Times Magazine
Atlassian	Fox (21st Century)	Soc. Qui. y Minera	Castlight Health	Toyota Motor
Autodesk	General Electric	Square	Cavium	TripAdvisor
BlackRock	General Mills	Starbucks Corp	Celgene Corp	Wayfair
Boeing	Gilead	T.J. Maxx	Citrix Systems	WPP
Box	Glu Mobile	Thermo.Fis,Scient.	Coca-Cola	
Bristol-Myers Sq.	Google	Time Inc.	Comcast	
Broadcom	GoPro	Twitter	Edwards Lifesc.	
Brocade Com. Syst.	HBO-Time Warner	United Continental	Eli Lilly	
Caleres	Hershey	United Tech.	Exxon Mobil	
Castlight Health	HP	United Technologies	Facebook	
Caterpillar	HSN	V F Corp	Fiat Chrysler	
CBS Corp	IBM	Washington Post	Financial Times	
Cemex	J&J	Wayfair	Ford	
Cisco	JPMorgan Chase	Workday Inc.	Fox (21st Century)	
CNN-Time Warner	Lockheed Martin	Yelp	General Electric	
Goldman Sachs	Macy's	Zynga	General Motors	
ConocoPhillips	Merck		Google	
CW Inc.	Microsoft		Harmonic Inc	
Delta Air Lines Inc	Netgear Inc.		Intel	
Dillard's	New Relic		L Brands	

Appendix C: Chapter 3

Table C.1 Definitions of the main variables

Variable	Variable Definitions
Total Return ($r_{i,t}$)	$r_{i,t}$ encounters for reinvesting the dividends back in the company and not distributing outside/to the shareholders.
Abnormal Return (*AR*)	*AR* is the difference between the actual rate of return of the stock considered and its ex-post expected rate of return over the whole length of the event window.
Cumulative abnormal return (*CAR*)	*CAR* is the sum of the abnormal returns over the whole length of the event window.
Previous days returns ($r_{i,t-j}$)	$r_{i,t-j}$ is the lagged dependent variable used to account for autocorrelation.
Monday effects ($WD_{k,t}$)	$WD_{k,\ t}$ is a dummy variable that equals 1 on the selected day of the week *k* (either Monday, Tuesday, Wednesday, or Thursday), and zero otherwise.
The turn-of-the-year effect (Tax_t)	Tax_t is a dummy variable that equals 1 on the first five trading days in January, and zero otherwise.
Event Effect and reversal effect ($E_{l,t}$)	$E_{l,t}$ with $l = 0 \dots 4$, stands for possible event effect – on the day of the nuclear accident - and reversal effect indicator – days following the nuclear accident day.
Size decile	Portfolio of securities sorted in deciles by their value of capitalization.
Small_Close (SC_i)	SC_i is a dummy variable equal to 1 if stock *i* is of small size (i.e. belongs to decile 6 to decile 10) and it is in the same state in which the nuclear accident occurs, and zero otherwise.
Big_Far (BF_i)	BF_i is a dummy variable equal to 1 if stock *i* is of large size (i.e. belongs to decile 1 to decile 5) and it is not in the same state in which the nuclear accident occurs, and zero otherwise.
Small_Far (SF_i)	SF_i is a dummy variable equal to 1 if stock *i* is of small size (i.e. belongs to decile 6 to decile 10) and it is not in the same state in which the nuclear accident occurs, and zero otherwise
VIX and VXO	*VIX* is a measure of the implied volatility of the S&P500 index option prices. *VXO* is a measure of implied volatility using 30-day S&P100 index option prices.
Close (C_i)	C_i is a dummy variable equal to 1 if stock *i* is in the same state in which the nuclear accident occurs.
Nuclear (Nuc_i)	Nuc_i is a dummy variable equal to 1 if stock *i* belongs to the nuclear energy industry.
Clean (Cl_i)	Cl_i is a dummy variable equal to 1 if stock *i* belongs to the clean energy industry.

Table C.2 Nuclear Accidents (event days)

The table reports detailed description of all 102 events taken into consideration in the period from 1944 to 2017. All events are sorted by date, type of event i.e. accident, then by location, and content. The U.S. Department of Defense defines "accidents involving nuclear weapons" as "unexpected events involving nuclear weapons or nuclear weapons components that result in any of the following: accidental or unauthorized launching, firing, or use, by U.S. Forces or supported allied forces, of a nuclear-capable weapon system which could create the risk of an outbreak of war; nuclear detonation; non-nuclear detonation or burning of a nuclear weapon or radioactive weapon component, including a fully assembled nuclear weapon, an unassembled nuclear weapon, or a radioactive nuclear weapon component; radioactive contamination; seizure, theft, or loss of a nuclear weapon or radioactive nuclear weapon component, including jettisoning; public hazard, actual or implied". The 102 events are later filtered to meet the non-overlapping properties as explained in Section 4.

Date	Type of nuclear accident	Event location	Event description
2 September 1944	Research Facility	USA	The Manhattan Project chemists, Peter Bragg and Douglas Paul Meigs, were killed in an attempt to unclog a tube in a uranium enrichment device. The explosion of radioactive uranium exploded at the Naval Research Laboratory in Philadelphia, PA.
21 August 1945	Research Facility	USA	Harry K. was killed during the final stages of the Manhattan Project. Harry was killed from a radiation burst released when a fissile material was handled unappropriately. This accident changed the way of how these components were handled.
21 May 1946	Research Facility	USA	Louis Slotin mistakenly dropped a screwdriver in the core for a Mark 3 nuclear bomb. Slotin died, and 8 people were exposed to radiation. It happened at the Los Alamos Scientific Laboratory in New Mexico.
29 November 1955	Research Facility	USA	The Experimental Breeder Reactor located in Idaho, partially melted down. It was operating in 1951 and was decommissioned in 1964, and at that time was the world's first nuclear power plant.
2 July 1956	Research Facility	USA	2 explosions destroyed a part of Sylvania Electric Products' Metallurgy Atomic Research Center in New York. Nine people were injured.
30 December 1958	Research Facility	USA	A scientist was exposed to radiation following an accident involving the mixing of plutonium solutions. The scientist died 35 hours later from the radiation.
26 July 1959	Research Facility	USA	A damaged coolant channel wasted 30% of the fuel elements at the Santa Susana Field Laboratory in California. It was later found that local residents did not do the damage. They successfully sued for $30 million over cancer abnormalities due to their close distance to the facility.
2 April 1962	Research Facility	USA	A nuclear excursion occurred in a plutonium-examining facility in Washington. Some employees were hospitalized due to close encounter with radiation, and radiation was found in the near atmosphere for sevearl days following the incident.
26 March 1963	Research Facility	USA	At an experimental facility in California, a mechanical failure led to a nuclear leak, and fire with serious damage to the shielded vault where the experiment was taking place.
5 October 1966	Research Facility	USA	A malfunction in a cooling system caused a meltdown at Detroit Edison's Enrico Fermi I reactor in Detroit. Radioactive gases were released but later contained. The acccident is documented in John Fuller's We Almost Lost Detroit.
11 January 1992	Research Facility	USA	Andrew Riley was killed when 1 cold fusion cell in a Menlo Park, CA, laboratory exploded while being moved. 3 other cells were buried on site, leading to rumors that a nuclear reaction had taken place. In a report was concluded that the accident was a chemical explosion.
June 2013	Research	USA	U.S. Department of Defense's Defense issued a report detailing numerous problems that took place at a nuclear plant

	Facility		used to generate electricity at the Antarctica base. A total of 438 malfunctions were documented bringing a lot of doubts of the functionality of the base.
3 January 1961	Power Plant	USA	The world's first atomic related fatalities happened following a reactor blast at the National Reactor Testing Station in Idaho.Three experts were killed, with radioactivity "largely confined".
24 July 1964	Power Plant	USA	Robert Peabody died due to exposure of extreme radiation at the United Nuclear Corp. fuel facility in Rhode Island, when liquid uranium which he was pouring went critical, starting a radioactive reaction.
19 November 1971	Power Plant	USA	Mississippi River got dumping of about 50,000 gallons of radioactive waste water from the water storage of Northern States Power Company's reactor in Monticello, Minnesota.
27 July 1972	Power Plant	USA	Two workers at the Surry Unit 2 facility in Virginia were fatally scalded after a routine valve adjustment led to a steam release in a gap in a vent line.
28 May 1974	Power Plant	USA	The AEC (Atomic Energy Commission) issyed a report stating that 861 "abnormal events" had occurred in 1973 in the nation's 42 operative nuclear power plants. About 12 of them involved the release of radioactivity "above average levels."
22 March 1975	Power Plant	USA	An expert checking for air leaks caused $100 million in damage when fire butst at the Browns Ferry reactor near Decatur, Alabama. The fire caused damage on the electrical controls, lowering the cooling water to minima, before the plant goes off.
28 March 1979	Power Plant	USA	A major accident occurred at 4:00 am at the Three Mile Island nuclear plant in Pennsylvania. A series of human and mechanical failures almost brought up a nuclear disaster. Somewhat by 8:00 a.m., after cooling system failed, the temperatures soared above 5,000 degrees, the top portion of the reactor's 150-ton core melted.
11 February 1981	Power Plant	USA	New employee working his first day accidentally opened a valve which led to the contamination of eight men by 110,000 gallons of radioactive coolant sprayed into the containment building of the Tennessee Valley Authority's Sequoyah I plant in Tennessee.
25 January 1982	Power Plant	USA	15,000 gallons of radioactive coolant spilled in the plant after a steam generator pipe broke at the Rochester Gas & Electric Company's Ginna plant in New York.
15-16 January 1983	Power Plant	USA	About 208,000 gallons of radioactive water was accidentally dumped into the Tennessee River from the Browns Ferry plant.
25 February 1983	Power Plant	USA	A catastrophic event was missed at the Salem 1 reactor in New Jersey when the plant was manually shut down after a failure of automatic shutdown systems to act properly.
9 December 1986	Power Plant	USA	4 out of 8 workers died after a feedwater pipe ruptured at the Surry Unit 2 facility in Virginia causing the workers to be scalded by a release of hot water and steam.
28 May 1993	Power Plant	USA	The NRC (Nuclear Regulatory Commission) published a warning to the operators of 34 nuclear reactors around the U.S. that the equipment used to measure water levels in the reactor could give false measurements during routine shutdowns and fail to detect leaks. The problem was reported as a common one, by an engineer at Northeast Utilities in Connecticut.
15 February 2000	Power Plant	USA	New York's Indian Point II power plant released a small amount of radioactive steam when an old generator broke down. The Nuclear Regulatory Commission first reported that there was no radioactive material released, but later changed their initial statement.
6 March 2002	Power Plant	USA	Technicians discovered a into the reactor vessel head at the Davis-Besse nuclear plant in Ohio. The water inside had corroded the metal that held back over 80,000 gallons of radioactive water.
7 January	Power	USA	The Vermont Department of Health was contacted by the officials at the Vermont Yankee Nuclear Power station in

2010	Plant		Vernon, Vermont because the samples taken from a monitoring well in November 2009 contained radioactive tritium at levels 37 times more from the federal limit.
31 January 2012	Power Plant	USA	A minor leak of radioactive steam happened after a crack in a tube at the San Onofre plant in California. Approximately 8.7% of the tubes in a replacement steam generator experienced damage due to a design flaw. The plant was permanently shuttered the following year.
13 February 1950	Bombs and Bombers	USA	Due to complicated by icing conditions on the way to Carswell Air Force Base in Fort Worth, Texas, the crew headed out over the Pacific Ocean to release the nuclear weapon from 8,000 feet off the coast of British Columbia.
11 April 1950	Bombs and Bombers	USA	Nuclear weapon was destroyed in the crash of a B-29 flying from Kirtland Air Force Base. The plane crashed into a mountain near Manzano Base in Albuquerque, New Mexico, killing 12 crewmembers aboard and 7 on the ground.
5 August 1950	Bombs and Bombers	USA	18 men died when a B-29 carrying Mark IV nuclear bombs faild to take-off from Fairfield-Suisun Air Force Base in California.
10 November 1950	Bombs and Bombers	USA	A B-50 route to Davis Monthan Air Force Base in Tucson, Arizona, was forced to jettison a nuclear weapon over the St. Lawrence River near St. Alexandre-de-Kamouraska, Canada.
10 March 1956	Bombs and Bombers	USA	An aircraft B-47 departing from MacDill Air Force Base in Tampa, Florida, vanished above the Mediterranean Sea, while carring two capsules of nuclear weapons fuel. Later conducted investigation didn’t succeed to find the aircraft or any of the crew or the capsules aboard.
27 July 1956	Bombs and Bombers	USA	An aircraft B-47 lost control and crashed into a storage igloo containing three nuclear bombs type Mark 6, while performing touch-and-go landing practices Lakenheath Royal Air Force Station near Cambridge, England. About 8,000 pounds of TNT was contained in each of the bombs’ trigger mechanism.
22 May 1957	Bombs and Bombers	USA	A B-36 bomber flying over an uninhabited area (possessed by the University of New Mexico) near Albuquerque, New Mexico has accidentally released a 10-megaton hydrogen bomb.
28 July 1957	Bombs and Bombers	USA	A C-124 Globemaster went through loss of power in two engines, while transporting a nuclear capsule and three nuclear weapons from Dover Air Force Base in Delaware to Europe. The crew dropped two of the weapons near east over Rehobeth, Del., and Cape May/Wildwood, New Jersey.
11 October 1957	Bombs and Bombers	USA	A B-47 taking of from Homestead Air Force Base in Florida crashed quickly while carrying a nuclear weapon. In the following fire the weapon was destroyed to some extent, however the nuclear core was retrieved undamaged. On the runway at the U.S. Strategic Air Command base 90 miles northeast of Rabat, Morocco, an aircraft B-47 bearing a nuclear weapon collapsed and ignited. The accidental explosion was denied by the U.S. State Department, announcing instead that "a practice evacuation" had taken place.
31 January 1958	Bombs and Bombers	USA	A B-47 bearing a Mark 15, Mod 0, nuclear bomb collided with an F-86 near Savannah, Georgia, while on a simulated combat mission from the Homestead Air Force Base in Florida. The B-47 crew dropped the nuclear bomb in the Atlantic Ocean near Savannah after three failed attempts to land at at Hunter Air Force Base in Georgia.
5 February 1958	Bombs and Bombers	USA	An unarmed nuclear weapon was inadvertently dropped into a garden owned by Walter Gregg and his family in Mars Bluff, South Carolina from a B-47 going from Hunter Air Force Base in Georgia to an overseas base. Gregg’s house was destroyed, and six family members were injured when the conventional explosives exploded.
11 March 1958	Bombs and Bombers	USA	A B-47 bearing a nuclear weapen ignited and crashed throughout a takeoff from Dyess Air Force Base in Abilene, Texas, causing the death of one crew member. A crater with 35 feet width and 6 feet depth was created when the conventional explosives exploded.
4 November	Bombs and	USA	A B-47 ingited at Chennault Air Force Base in Lake Charles, Louisiana on the ground, demolishing a nuclear weapon

1958	Bombers		conveyed. The nearby area had a minor radioactive contamination.
26 November 1958	Bombs and Bombers	USA	A C-124 with a nuclear weapon onboard crashed during taking off at the Barksdale Air Force Base in Louisiana, creating a radioactive contamination in the immediate vicinity.
6 July 1959	Bombs and Bombers	USA	While performing a mid-air refueling, a B-52 bomber with two nuclear weapons on board and a KC-135 jet tanker crashed over Hardinsburg, Kentucky, shortly after takeoff from Columbus Air Force Base in Mississippi. Four out of eight of the B-52 crew were killed, as well as all four members of the tanker crew.
15 October 1959	Bombs and Bombers	USA	A BOMARC-A nuclear missile exploded after its fuel tank ruptured by an explosion of a high-pressure helium tank at McGuire Air Force Base in New Egypt, New Jersey. The melting of the missle caused plutonium contamination in the facility and in the ground water below, because of the runoff from firefighting water.
7 June 1960	Bombs and Bombers	USA	A B-52 bomber disintegrated in midair following an engine fire and explosion, while bearing one or more nuclear weapons around 10 miles north of Monticello, Utah. All five crewmembers were killed.
21 January 1961	Bombs and Bombers	USA	A B-52 bomber went through a structural failure and disintegrated in mid-air, releasing two hydrogen bombs, 12 miles north of Seymour Johnson Air Force Base in Goldsboro, NC. Three of the crew members died in the mid-air explosion, while five parachuted to safety.
24 January 1961	Bombs and Bombers	USA	A B-52 carrying two nuclear weapons on board crashed in Yuba City, California in the middle of a training mission following depressurization of the crew cabin. The commander stayed aboard to lead the aircraft away from populated areas until it descended to 4,000 feet altitude, while the othter members of the crew bailed out at 10,000.
14 March 1961	Bombs and Bombers	USA	A B-52D crashed 17 miles southwest of Cumberland, Maryland, while on end route from Westover Air Force Base in Massachusetts to Turner Air Force Base in Georgia. The two nuclear weapons on board were recovered undamaged, however three of the five members of the crew were killed.
13 January 1964	Bombs and Bombers	USA	A B-58 slid off an iced runway at Bunker Hill (now Grissom) Air Force Base in Peru, Indiana, resulting in fire which consumed parts of the five aboard nuclear weapons, which lead to radioactive contamination in the nearby area.
8 December 1964	Bombs and Bombers	USA	A welder working at a Titan missile silo outside Searcy, Arkansas, hit a hydraulic line by accident, resulting in fire and power outage, causing deaths of 53 workers.
9 August 1965	Bombs and Bombers	USA	53 workers died after a welder hit a hydraulic line which led to a fire at the Titan missile silo outside Searcy, Arkansas.
5 December 1965	Bombs and Bombers	USA	An incident occurred near the Pacific Ocean, some 200 miles east of Okinawa. An A-4E aircraft fell off the USS Toconderoga, with the loss of pilot Lt. Webster and 1 atomic weapon.
17 January 1966	Bombs and Bombers	USA	11 crew men died when a B-52 collided with an Air Force KC-135 jet tanker while refueling over Spain. The incident led to igniting the KC-135's 40,000 gallons of jet fuel. Two hydrogen atomic bombs were damaged, releasing radioactive particles over the fields of Palomares. Third bomb landed intact near the village of Palomares. The 4th bomb was lost at sea. It took thousands of men working for 4 months to recover the bomb. About 1,400 tons of radioactive soild and vegetation were recycled to the U.S. for burial. The U.S. was sued by 522 Palomares residents later, at a cost of $600,000, who further got a gift of a $200,000 desalinizing plant.
22 January 1968	Bombs and Bombers	USA	A B-52 crashed 7 miles south of Thule Air Force Base in Greenland, releasing radioactive fragments of 3 hydrogen bombs and dropping 1 bomb into the ocean. The contaminated ice and airplane parts were sent back to the U.S., with some of the bomb fragments going back to the manufacturer in Amarillo, Texas.
19 September 1980	Bombs and Bombers	USA	An accident happened when an Air Force repairman doing routine maintenance in a Titan II ICBM silo in Damascus, Arkansas dropped a wrench socket. Explosion occurred and killed one specialies and injured 21 others.

2 November 1981	Bombs and Bombers	USA	During a transfer operation in Scotland, a fully-armed Poseidon missile was accidentally dropped 17 feet from a crane while trying to fit the missile on a U.S. submarine.
18 April 1959	Submarines and Ships	USA	A 33,000 curies of radioactive material were dumped in the ocean. It was from an experimental sodium-cooled reactor in Maryland. The reactor was damaged and was dumped.
10 April 1963	Submarines and Ships	USA	129 men were killed after a nuclear submarine exploded during a test dive east of Boston.
5 December 1965	Submarines and Ships	USA	An A-4E Skyhawk strike airplane carrying an atomic warhead fell off an elevator on the U.S. aircraft carrier Ticonderoga and rolled off into the ocean. Since the bomb was lost at a depth of 16,000 feet, Pentagon feared that water pressure could have caused the atomic bomb to explode. It is still unknown what happened to the bomb, plane, the pilot.
22 May 1968	Submarines and Ships	USA	The U.S.S. Scorpion mysteriously disappeared on this day. It was a nuclear-powered attack submarine carrying 2 Mark 45 ASTOR torpedoes.
14 January 1969	Submarines and Ships	USA	17 dead and 85 injured after a series of aircraft explosions.
16 May 1969	Submarines and Ships	USA	$50 million nuclear submarine sank to the bottom since the Navy was "inexcusable carelessness", the House Armed Services said.
12 December 1971	Submarines and Ships	USA	While transferring 500 gallons of radioactive coolant water an accident spilled the water into the Thames River near New London, Connecticut.
22 May 1978	Submarines and Ships	USA	Various health partners joined to build more effective systems for health in contaminated countries.
26 April 1953	Tests-Other	USA	Above-ground nuclear tests in Troy, New York resulted in radioactive rain.
5 September 1961	Tests-Other	USA	Resumption was ordered by President Kennedy of the nuclear testing, "underground, with no fallout."
10 December 1961	Tests-Other	USA	Several New Mexico highways were closed due to radioactive clouds escaping from an underground nuclear test facility.
4 June 1962	Tests-Other	USA	The Bluegill atomic test was stopped 10 minutes after launch because of tracking system malfunctioning. The nuclear equipment was lost in the ocean.
20 June 1962	Tests-Other	USA	Radioactive contamination scattered across Johnston Island in the Pacific Ocean as a result of a failure of the Starfish nuclear test.
15 October 1962	Tests-Other	USA	Plutonium contamination in Johnston Island took place as a result of another failed missile test.
9 December 1968	Tests-Other	USA	Clouds as a result of a radioactive nuclear test in Nevada broke through the ground. It violated the Limited Nuclear Test Ban Treaty signed 5 years before the test.
18 December 1970	Tests-Other	USA	A radioactive cloud over Wyoming appeared, as a result of an underground nuclear test in Nevada.
15 July 1999	Tests-Other	USA	During the last 50 years, thousands of employees were exposed to toxic and radioactive contamination at U.S. nuclear weapons facilities, a spokesperson for President Clinton announced. They can seek government compensation for related illnesses.
11 September	PSSD	USA	Serious release of plutonium dust and smoke into the atmosphere occurred after a fire at the Rocky Flats Nuclear

1957			Weapons Plant in Colorado.
13 November 1963	PSSD	USA	Three workers were injured, and small radioactive contamination took place after 123,000 pounds of high explosives (parts of old nuclear weapons being disassembled) detonated at the AEC storage facility in Texas.
11 May 1969	PSSD	USA	A radioactive plutonium fire started in Building 776 at the AEC's Rocky Flats Nuclear Weapons Plant. The radioactive material was released into the atmosphere which later appeared on the firefighters' boots, and several building walls which later had to be dismantled.
16 July 1979	PSSD	USA	New Mexico, after a dam-tailings broke, 100 million gallons of radioactive liquids were released downstream at Church Rock.
21 September 1980	PSSD	USA	Two barrels with radioactive materials were lost during transportation on New Jersey's Route 17. The driver noticed the missing barrels only after arriving in Albany, New York.
6 January 1986	PSSD	USA	One worker died, and 130 others asked for medical treatment after a container of toxic gas exploded at The Sequoyah Fuels Corp. uranium processing factory in Oklahoma.
6 June 1988	PSSD	USA	70,000 medical supply containers were recycled as they had been exposed to radiation after the leak of Cesium-137 at the Radiation Sterilizers, Georgia.
24 November 1992	PSSD	USA	Over the 22 years of operation, the Sequoyah Fuels Corp included an accident in 1986 that killed one worker and contaminated the Arkansas River. The factory was closed by order from the Government.
31 March 1994	PSSD	USA	Three fire fighters, three reactor operators, and one technician were contaminated after a fire broke up at a nuclear research facility on Long Island, New York. Above average amounts of radioactive substances were also released into the nature arround.
8 August 1999	PSSD	USA	At the Department of Energy's Paducah Gaseous Diffusion Plant in Kentucky, thousands of workers were exposed to radiation over a 23-year period, reported the *Washington Post*.
14 February 2014	PSSD	USA	21 employees forced to evacuate after a 55-gallon radioactive waste burst open at the Waste Isolation Pilot Plant outside Carlsbad, New Mexico. The facility was shutted down.
30 August 1976	Hanford case	USA	Off-scale measurements after a chemical explosion at Hanford. One worker is found to be injured from radioactive Americium 241.
9 May 2013	Hanford case	USA	Scientific American: 60 of 177 radioactive underground tanks were found to be leaking.
9 May 2017	Hanford case	USA	Temporary evacuation after a tunnel storring highly radioactive chemical waste and radioactive equipment collapsed.
31 August 1985	Fukushima	Japan	Fire broke up after a routine shutdown at Fukushima nuclear power plant.
8 February 1991	Fukui	Japan	After an emergency release valve failed radioactivity was released from Fukui nuclear power plant.
22 February 1993	Fukushima	Japan	Due to high-pressure steam, 1 worker killed and 2 injured.
11 March 1997	Tokaimura	Japan	Thirty-seven employees were exposed to radiation in the Tokaimura nuclear reprocessing plant fire and explosion.
9 August 2004	Mihama	Japan	Massive inspection program after a serious lack in inspection in Japanese uclear plants took place as a result of a steam explosion at the Mihama-3.

16 July 2007	Kashiwazaki	Japan	Radioactive water spilled into the Sea of Japan after a severe earthquake in the region where Tokyo Electric's Kashiwazaki-Kariwa Nuclear Power Plant is located.
11 March 2011	Fukushima	Japan	Fukushima Daiichi reactors went into shutdown after Japan was shaken by a major earthquake.
6 June 2017	Ibaraki	Japan	The incident occurred at the Japan Atomic Energy Agency's Oarai Research and Development Center, after a bag containing radioactive material tore open while a check on radioactive storage inside a "controlled" room was performed.
17 October 1969	Saint-Laurent	France	Inside the A1 reactor 50 kg of uranium dioxide melted.
25 July 1979	Saclay	France	Radioactive fluids were released into the drains designed for ordinary wastes, seeping into the local watershed at the Saclay BL3 Reactor.
13 March 1980	Loir-et-Cher	France	Saint Laurent A2 reactor shutdown after a malfunctioning of the cooling system for fuses fuel.
12 April 1987	Tricastin	France	7 workers injured and contaminated water supplies after Tricastin fast breeder reactor leaks coolant, sodium and uranium hexachloride.
27 December 1999	Blayais	France	An unexpectedly strong storm floods the Blayais Nuclear Power Plant, forcing an emergency shutdown after injection pumps and containment safety systems fail from water damage.
13 July 2008	Tricastin	France	Contaminated of wastewater - primarily with uranium, was accidentally poured in the soil and runoff into the nearby river.
5 April 2012	Penly	France	Fire in the second reactor followed by small and neglective radioactive leak inside the pump.

Source : www.defense.gov/
www.lutins.org/nukes.html
www.whistleblower.org

Table C.3 U.S. Nuclear Energy Companies

This table lists the U.S. publicly listed Nuclear Energy companies on NYSE and NASDAQ Composite which are regarded as having exposure to the events in my sample. The total number of companies is 25 and it is obtained by the following selection procedure. First, I select the companies by status: I am interested in *active and publicly listed* companies. Second, I further select the companies that have a domicile in the U.S. Third, I set up the *period of operation* of the companies from 1944 to 2017. The data is obtained from Bloomberg's database.

NAME OF THE COMPANY	TICKER
Ameren Corp	AEE
American Electric Power	AEP
BWX Tech	BWXT
Constellation Energy Grip	CEG
Dominion Resources	D
DTE Energy	DTE
Duke	DUK
DuPont Company	DD-B
Edison International	EIX
El Paso Electric	EE
Entergy Co	ETR
Exelon Corp.	EXC
FirstEnergy Corp.	FE
Lithium Corp. of America	LAC
Monsanto Chemical	MON
Nextera	NEE
NRG Energy	NRG
PG&E Corp.	PCG
Pinaccle West Capital Corp	PNW
PPL Corp	PPL
Progress Energy	PGN
Public Service Ent. Corp	PEG
Souther Co	SO
Stepan Company	SCL
Xcel Energy	XEL

Table C.4 U.S. Clean Energy Companies

This table lists the U.S. publicly listed Clean Energy companies on NYSE and NASDAQ Composite which are regarded as having exposure to the events in my sample. The total number of companies is 17 and it is obtained by the following selection procedure. First, I select the companies by status: I am interested in *active and publicly listed* companies. Second, I further select the companies that have a domicile in the U.S. Third, I set up the *period of operation* of the companies from 1944 to 2017. The data is obtained from Bloomberg's database.

NAME OF THE COMPANY	TICKER
Ascent Solar Technologies	ASTI
Atlantica Yield	AY
Canadian Solar	CSIQ
Covanta holding	CVA
Ener1	HEV
Energy Conversion Devices	ENER
First Solar	FSLR
Hoku	HOKU
JinkSolar	JKS
Pattern Energy	PEGI
Plug Power	PLUG
Razer Technologies	RZTI
Renewable Energy	REGI
Solaredge tech	SEDG
Sunpower	SPWR
Sunrun	RUN
Terraform Power	TERP

Appendix D: Summary in Slovenian language / Daljši povzetek disertacije v slovenskem

Motivacija za disertacijo

Ekonomisti že dolgo trdijo, da cene delnic izboljšujejo razporeditev kapitala z zbiranjem razpršenih informacij in izpostavljanjem najobetavnejših možnosti za vlaganje. Čeprav so mnogi vidiki razmerja med delniškim trgom in gospodarstvom že bili raziskani, pa obstoječe teorije še ne vključujejo vseh členov verige od delovanja delniških trgov do širjenja informacij. Podjetja širom sveta čutijo vpliv gospodarskega okolja, v katerem poslujejo. Kakršna koli sprememba poslovnega okolja ima določen učinek na ravnanje firme. Informacije same po sebi igrajo pomembno vlogo pri oblikovanju poslovnega okolja. Spontanost informacij in asimilacija poslovnih entitet – v kakršni koli poslovni transakciji – vplivata na podjetje ali na vrednost podjetja (D'Avolio, 2002). Prenos informacij do podjetja kot entitete je eden izmed glavnih oblikovalcev gibanja delniških trgov. Drug pojav, ki je zelo pomemben za razumevanje finančnih trgov, je način, kako vlagatelji pridobivajo informacije (Edmans et al., 2007).

Upoštevaje, da so mediji vedno bolj ključni viri širjenja informacij o finančnih trgih, je namen te doktorske disertacije analiza in ovrednotenje odnosa med širjenjem informacij in njegovim vplivom na donosnost delnic. V preteklosti so ta odnos raziskovali Klibanoff et al. (1998), Tetlock et al. (2008), Fang in Peress (2009) ter Boulland et al. (2016). Klibanoff et al. (1998), na primer, ki so opravili ogromno dela na tem področju, so prišli do spoznanja, da vlagatelji pripisujejo večji pomen novicam, ki so jim mediji posvetili več pozornosti, kot tistim, ki so jim mediji posvetili manj pozornosti, četudi so novice imele enako temeljno vrednost. Natančneje so Klibanoff et al. (1998) zbirali novice za posamične države z domače strani časnika *New York Times* in preverjali napačno razumevanje vlagateljev, pri čemer so vlagatelji nepravilno zaznavali temeljne signale ob napovedovanju prihodnjih temeljnih signalov. Ugotovili so, da se nekateri vlagatelji bolj odzovejo na temelje po bolj naznanjenih/obravnavanih novicah, s čimer vplivajo na cene in jih približujejo vzorcu danega temelja.

Tetlock et al. (2008), ki so raziskovali interakcije med razširjenimi vsebinami medijev in donosnostjo delniškega trga, so prav tako pripomogli k razvoju tega področja raziskovanja. Zgradili so model analize šuma in jezikovne vsebine po DeLong et al. (1990a) in Campbell et al. (1993) ter tako dokazali, da velik delež medijskega pesimizma signifikantno napoveduje padce cen na trgu. Poleg tega je eden izmed dragocenih pridobljenih vpogledov ta, da je velik obseg trgovanja povezan z nenavadno visoko ali nizko vrednostjo medijskega pesimizma. Nazadnje so Tetlock et al. (2008) ugotovili, da je nizka tržna donosnost povezana z visoko medijsko pobitostjo.

Fang in Peress (2009) dodajata svoje delo glede medijske pokritosti in preseka delniških donosov. Razsvetljujeta moč medijev nad finančnimi trgi s pomočjo raziskovanja premij delniškega donosa za delnice z medijsko pokritostjo in brez nje. Spoznala sta, da povprečno delnice, ki niso medijsko pokrite, pridobijo 0,20 % vrednosti na mesec več kot tiste, ki so pogosteje v medijih. Nedavno sta Engelberg in Parsons (2011) prav tako analizirala vzročno razmerje med medijsko pokritimi novicami in odzivom delniških trgov. Poglavitna razlika med njuno raziskavo in tisto, ki sta jo izvedla Fang in Peress (2009), je meritev medijskega učinka na donosnost delnic na lokalni ravni. Ugotovila sta, da medijska pokritost v lokalnih medijih poveča obseg trgovanja lokalnih vlagateljev za približno 50 %. Njune ugotovitve jasno kažejo, da medijska pokritost vzpodbuja lokalno trgovanje in da je geografska bližina pomembna zaradi interesov lokalnih vlagateljev v določen vrednostni papir (glej tudi Boulland et al., 2016).

Glede na obsežno obstoječo raziskovalno gradivo na področju razmerja med mediji kot virom širjenja informacij in finančnimi trgi, ta disertacija poskuša zapolniti vrzeli v strokovni literaturi predvsem s teh treh vidikov:

1) s proučevanjem odziva cene delnic na geografsko bližino informacije finančnim trgom;
2) s proučevanjem vloge političnih akterjev, ki se izdajajo za kredibilen vir širjenja informacij, in njihovega vpliva na obnašanje finančnih trgov;
3) s proučevanjem odziva finančnih trgov, razpoloženja vlagateljev in učinkov panoge na dramatične dogodke, kot je jedrska nesreča ali izbruh ebole.

Splošna diskusija in zaključek

To poglavje nudi pregled glavnih ugotovitev in utemeljuje tako teoretičen kot empiričen doprinos disertacije. Glavni namen te doktorske disertacije je opazovanje, preverjanje in ovrednotenje odnosa med širjenjem informacij v finančnih trgih in predvsem vplivom na donosnost delnic podjetij. Preostanek poglavja je strukturiran tako: najprej povzema ugotovitve posamičnih poglavij doktorske disertacije, nato obravnava glavni doprinos in na koncu povzame disertacijo.

Povzetek glavnih ugotovitev

V 1. poglavju se osredotočam na ovrednotenje učinka širjenja informacij na finančna tržišča, kjer določen dogodek služi kot vir informacij. V tem poglavju sem obravnaval naslednja raziskovalna vprašanja.

Raziskovalno vprašanje 1.1: Ali ima geografska bližina informacij (razširjenih ob izbruhu ebole) statistično signifikanten vpliv na finančne trge?

Raziskovalno vprašanje 1.2: Ali je učinek dogodka na donosnost delnice močnejši za manjša *glede na večja podjetja?*

Raziskovalno vprašanje 1.3: Ali je učinek na dan dogodka (tj. na dan 0) večji za bolj volatilne delnice kakor za manj volatilne?

Raziskovalno vprašanje 1.4: Kako (pozitivno ali negativno) vpliva izbruh ebole na posamične poslovne panoge v ZDA?

Raziskovalno vprašanje 1.5: Ali vpliva izbruh ebole na podjetja, ki so bolj medijsko izpostavljena, bolj kot na podjetja, ki so medijsko manj izpostavljena?

Na kratko v 1. poglavju preverjam, ali je geografska bližina razširjenih informacij o izbruhu ebole v obdobju 2014–2016 v povezavi z intenzivno medijsko pokritostjo vplivala na cene delnic v ZDA. V 1. poglavju so delniške družbe ZDA razporejene glede na izpostavljenost njihovega poslovanja. Prav tako so razporejeni posamični dogodki v zvezi z izbruhom ebole glede na kraj pojave.

V 1. poglavju so navedeni dokazi, da je izbruh ebole imel največji vpliv na podjetja, katerih poslovanje je izpostavljeno zahodnoafriškim državam in ZDA pri dogodkih v zahodnoafriških državah in ZDA. Poleg tega v 1. poglavju nadaljujem z raziskovanjem, ali obstaja razlika v razsežnosti učinka na portfelje, razporejene po višini kapitalizacije. Ugotovitve potrjujejo, da je negativni učinek izbruha ebole izrazitejši za manjše vrednostne papirje glede na večje. Nazadnje v 1. poglavju raziskujem, ali je izbruh ebole posredno vplival na razpoloženje vlagateljev preko implicitne volatilnosti, vrednostnih papirjev določenih panog in vrednostnih papirjev, močno izpostavljenih v medijih. Ugotovitve kažejo, da je učinek še posebej izrazit za volatilnejše delnice, vrednostne papirje, izpostavljene intenzivni medijski pokritosti, in vrednostne papirje iz panog oprema za zdravstvo, farmacija in letalstvo.

V 2. poglavju vzpostavim povezave med financami in politiko, da lahko raziščem vpliv širjenja informacij na donosnost delnic podjetij. Vsebina poglavja se ravna po naslednjih raziskovalnih vprašanjih.

Raziskovalno vprašanje 2.1: Kateri dejavniki opisujejo verjetnost, da bo Trump omenil neko podjetje v obdobju od junija 2015 do junija 2017?

Raziskovalno vprašanje 2.2: Ali uporabljen ton v Trumpovih izjavah lahko napove donosnost delniškega trga, vpliva na obseg poslovanja in volatilnost cen delnic?

Raziskovalno vprašanje 2.3: Ali bi lahko politični dejavniki, kot na primer donacije določeni stranki in poslovne povezave predsedniškega kandidata z določenim podjetjem, vplivali na *delnice podjetja?*

V 2. poglavju natančneje ovrednotim politično moč predsednika Trumpa nad finančnimi trgi, ki jo je izvajal z izjavami na družbenih omrežjih v času predsedniških volitev leta 2016 v ZDA. S pomočjo logistične regresijske analize raziščem dejavnike, ki vplivajo na verjetnost, da bo Trump podjetje omenil v tvitu ali v novicah v obdobju volitev.

Ugotovitve kažejo, da je bolj verjetno, da Trump omeni podjetja, ki so mu poznana, s katerimi že ima poslovni odnos, so velika in so prisotna na mednarodnem trgu. Poleg tega je iz ugotovitev razvidno, da so Trumpove izjave imele izrazitejši in negativnejši učinek po volilnem dnevu kot pred njim.

Da bi lahko dodatno pojasnil vpliv Trumpovih izjav, uporabim v 2. poglavju presečno regresijsko analizo. Presečna analiza vključuje: čas izjave (tj. pred ali po predsedniških volitvah leta 2016); ton izjave na družbenem omrežju (tj. negativen oz. nenegativen); velikost, dobičkonosnost, vpliv in raven tveganja podjetja; ter politično usmerjenost podjetja in njihovo povezavo s Trumpom. Ugotovitve potrjujejo verjetnost vpliva političnih dejavnikov in poslovnih odnosov podjetij s Trumpom na delnice, obseg poslovanja in volatilnost delnic podjetja. Število povezovalnih kanalov, preko katerih je določeno podjetje povezano s Trumpom, se je prav tako izkazalo kot signifikanten dejavnik, ki pozitivno vpliva na nenormalen kumulativen donos podjetja.

V 3. poglavju raziskujem, ali širjenje informacij o dramatičnih dogodkih, kot so jedrske nesreče, vplivajo na finančne trga ZDA. V 3. poglavje se ravnam po naslednjih raziskovalnih vprašanjih.

Raziskovalno vprašanje 3.1: Ali ima geografska bližina informacij statistično signifikanten vpliv na finančne trge ob upoštevanju donosnosti delnic delniških družb, ki poslujejo v ZDA, kot posledica jedrskih nesreč, ki so se zgodile v ZDA, Franciji in na Japonskem?

Raziskovalno vprašanje 3.2: Ali je učinek dogodka na donosnost delnice močnejši za manjša glede na večja podjetja?

Raziskovalno vprašanje 3.3: Ali jedrske nesreče vplivajo na implicitno volatilnost na dan nesreče?

Raziskovalno vprašanje 3.4: Kako (pozitivno ali negativno) vpliva jedrska nesreča na posamične poslovne panoge?

Raziskovalno vprašanje 3.5: Ali obstaja vpliv nesreče preko strahu, ki pri vlagateljih sproži strah in slabo razpoloženje, kar še dodatno znižuje cene delnic?

Konkretneje, v 3. poglavju beležim statistično signifikanten vpliv jedrskih nesreč na delniške družbe v ZDA v obdobju od 1944 do 2017. V 3. poglavju se lotevam težave s stališča vedenjskih financ, kar kaže, da dramatični dogodki, kot so jedrske nesreče, lahko povečajo strah in nenaklonjenost tveganju vlagateljev in posledično vplivajo na razpoloženje vlagateljev.

Ugotovitve kažejo, da geografska bližina informacij finančnemu trgu povečuje pomembnost dogodka (v zvezi z jedrskimi nesrečami v obdobju 1944–2017) in njegov vpliv na donosnost delnic podjetja. Nadalje kažejo ugotovitve, da je učinek dogodka velik, statistično signifikanten in negativen za ameriška podjetja, če se jedrska nesreča zgodi v ZDA; hkrati pa izkazujejo, da delnice dan po dogodku doživijo preobrat v zvezi z donosnostjo.

Dodatni preizkusi, ki sem jih izvedel v 3. poglavju, razkrivajo različen vpliv jedrskih nesreč glede na velikost in panogo podjetja. Ob koncu 3. poglavje predstavlja povečanje implicitne volatilnosti na dan jedrske nesreče; ugotovitve potrjujejo obstoj kanala strahu, preko katerega jedrske nesreče sprožajo strah pri vlagateljih, ki prispeva k dodatnemu padcu cen delnic.

Doprinos

Doprinos 1. poglavja je predvsem na področju vedenjskih financ. Konkretneje doprinaša k literaturi z opazovanjem odnosov med izpostavljenostjo podjetja različnim geografskim področjem poslovanja, medijsko pokritostjo dramatičnih dogodkov, velikostjo in panogo podjetja, strahom in tesnobo, ki jo izzovejo zadevni dogodki, ter nenaklonjenostjo tveganju vlagateljev, kadar sta strah in tesnoba povečana.

V 1. poglavju je v središču vpliv izbruha ebole na finančne trge z namenom analize širjenja informacij ob upoštevanju pomembnost geografske bližine dogodka. To poglavje je tesno povezano z analizo, ki so jo opravili Donadelli et al. (2016b), ki se ukvarja z globalnimi nevarnimi boleznimi in njihovim vplivom na donosnost delnic farmacevtskih podjetij.

V povezavi s sklopom literature, ki raziskuje učinek razpoloženja vlagateljev na finančne trge, je 1. poglavje tesno povezano z raziskavo, ki sta jo izvedla Kaplanski in Levy (2010a, 2010b), ter raziskavo, ki sta jo izvedla Cen in Liyan-Yang (2013); le-ti predstavljata nov vpogled glede vloge geografske bližine informacij na finančne trge in njihov psihološki učinek na postopek odločanja vlagateljev. Zaključki 1. poglavja predstavljajo dokaze, da je jasna zveza med relevantnostjo izbruha ebole odločitvam vlagateljev in razsežnostjo učinka dogodka.

To poglavje prav tako doprinaša literaturi opazovanje učinka medijske pokritosti na razpoloženje vlagateljev ob upoštevanju geografske bližine informacije finančnim trgom. V 1. poglavju uporabljeni študija dogodka in presečna metodologija ter ugotovitve poglavja so povezane z raziskavami, ki so jih izvedli Fang in Peress (2009), Engelberg in Parsons (2011) ter Peress

(2014), kjer so ugotovili, da vlagatelji bolj reagirajo na medijsko pokrite dogodke in bolj upoštevajo delnice in novice/dogodke, ki so jim fizično bližje.

Osrednji doprinos 2. poglavja literaturi je razvoj rešitve in premagovanje težav, ki so povezane s kredibilnostjo družbenih omrežij kot virom informacij. Sodelovanje na družbenih medijih ni nadzorovano, zato lahko kdorkoli ustvari uporabniški račun na katerem izmed omrežij in anonimno deli želene informacije. Kdorkoli lahko, na primer, ustvari uporabniški račun na Twitterju in tvita o poljubnem trgovanju z delnicami na finančnih trgih. Ob upoštevanju tega so informacije s Twitterja le omejeno uporabne za koristno analizo, saj so lahko namerno ali nenamerno zavajajoče.

Dodaten pomemben doprinos 2. poglavja literaturi je raziskava odnosa med ameriškimi politiki ter ameriškim gospodarstvom in finančnimi trgi. S tega stališča je 2. poglavje povezano z raziskavo ekipe Wagner et al. (2017), ki so opazovali pričakovanja v zvezi z uresničevanjem politične agende predsednika Trumpa pred volitvami in njihove učinke po volitvah. Vsebina 2. poglavja nudi dragocene dokaze o tem, da finančni trgi odražajo pričakovanja vlagateljev glede gospodarske rasti, obdavčevanja in trgovinske politike.

Še en sklop raziskav (Addoum in Kumar, 2016; Julio in Yook, 2012; Boutchkova et al., 2012), ki se povezane z 2. poglavjem, se osredotoča na stališče vlagateljev in ugotavlja, da vlagatelji spremenijo sestavo svojih portfeljev, podjetja zmanjšajo svoje kapitalske naložbe in volatilnost delniškega trg naraste pred nacionalnimi volitvami. V skladu s temi spoznanji 2. poglavje doprinaša ugotovitev, da je delniški trg občutljiv na politične novice, saj lahko predsedniški kandidat, ki morda sploh ne bo izvoljen, vpliva na gibanje vrednostnih papirjev glede donosnosti, obsega trgovanja in volatilnosti cen delnic.

Predsednik Trump je v javni politični svet kot državni voditelj vnesel do zdaj še ne videna dejanja. Povezana literatura, ki specifično analizira Trumpova samostojna dejanja, in se navezuje na 2. poglavje, je Huang in Low (2017), kjer simulirata komunikacijski slog, videz in osebne geste Donalda J. Trumpa s pomočjo igre bitka med spoloma. S tega stališča 2. poglavje doprinaša ugotovitve, ki kažejo na obstoj unikatnega komunikacijskega sloga brez primere, ki ga uporablja Trump. Tukaj 2. poglavje prikazuje negativen jezikovni ton političnih govorov kot prognozo negativne donosnosti delnic.

Zaključno 2. poglavje doprinaša znanosti analizo povezav med politiki in vodstvenim kadrom podjetij. Ugotovitve kažejo, da so, vsaj po mnenju vlagateljev, povezave med politiki in upravo podjetja lahko velikega pomena za podjetje. V povezavi z literaturo, ki raziskuje učinek razpoloženja vlagateljev na finančne trge, se 2. poglavje močno navezuje na raziskavo dvojca Kaplanski in Levy (2010b), ki prikazuje, da lahko nekateri dogodki ustvarijo negativno razpoloženje v dneh po dogodku. To poglavje v tem smislu predstavlja nova spoznanja glede vloge predsedniške signalizacije in širjenja informacij za finančne trge ter psihološkega učinka na postopek odločanja vlagateljev.

Doprinos 3. poglavja je analiza vpliva jedrskih nesreč na finančne trge v daljšem časovnem obdobju (od leta 1944 do 2017). Poleg tega poskuša ovrednotiti vpliv teh nesreč na finančne trge z namenom analize širjenja informacij po raznih vplivnih kanalih v povezavi z bližino dogodka.

V povezavi s sklopom literature, ki raziskuje učinek razpoloženja vlagateljev na finančne trge, je to poglavje tesno povezano z raziskavo, ki sta jo izvedla Kaplanski in Levy (2010a, 2010b), ter raziskavo, ki so jo izvedli Donadelli et al. (2016a); le-ti predstavljata nov vpogled glede vloge geografske bližine informacij na finančne trge in njihov psihološki učinek na postopek odločanja vlagateljev. Zaključki 3. poglavja predstavljajo dokaze, da obstaja jasna zveza med jedrskimi nesrečami, odločitvami vlagateljev in razsežnostjo učinka dogodka.

Poleg tega 3. poglavje predstavlja občuten doprinos literaturi z opazovanjem učinka medijske pokritosti na razpoloženje vlagateljev v povezavi z geografsko bližino informacijo finančnim trgom. Ugotovitve se navezujejo na raziskave avtorjev Engelberg in Parsons (2011), Peress (2014) ter Donadelli (2015), ki so odkrili, da vlagatelji bolj reagirajo na medijsko pokrite dogodke ter so pozornejši na delnice in novice/dogodke, ki so jim fizično bližje, kakor tudi na dogodke, ki pri vlagateljih sproža strah.

Na koncu 3. poglavje predstavlja še doprinos v smislu analize tržnega obnašanja vlagateljev in nagnjenosti teh k tveganju ter implicitne volatilnosti vrednostnih papirjev v obdobju okoli jedrskih nesreč. S tega stališča se ugotovitve navezujejo na delo avtorjev Baker in Wurgler (2007) ter Mehra in Sah (2002); ugotovitve potrjujejo spoznanje, da strah in tesnoba tvorita pozitivno zvezo z nagnjenjem vlagateljev k tveganju. Retrospektivno lahko ugotovimo, da se raziskovalna dejavnost tesno giblje ob raziskavi Donadelli et al. (2016b), ki so preverjali, ali je indeks strahu – posredni kazalnik razpoloženja vlagateljev, na katerega vplivajo dramatični dogodki kot so bolezni – vključen v vrednost delnic podjetij v določenih panogah; Donadelli et al. (2016b) sicer argumentirajo, da dogodki, kot so globalne bolezni, ne bi smeli motiti racionalnega trgovanja.

Zaključek

V tej doktorski disertaciji analiziram vlogo in vpliv širjenja informacij na finančnih trgih in predvsem učinek širjenja informacij na donosnost delnic podjetja. Najprej v disertaciji obravnavam, ali je geografska bližina razširjenih informacij v času izbruha ebole leta 2014–2016 v povezavi z intenzivno medijsko pokritostjo vplivala na cene delnic v ZDA. Nato analiziram, ali je učinek dramatičnih dogodkov (tj. izbruhi bolezni, jedrske nesreče) izrazitejši za podjetja določene velikosti za bolj volatilne delnice, delnice določenih panog in intenzivno medijsko izpostavljene delnice. Sledi razširitev skupnega področja politike in financ, kjer ovrednotim politično moč predsednika Trumpa nad finančnimi trgi skozi izjave na družbenih omrežjih v obdobju predsedniških volitev leta 2016 v ZDA. Zaključim s pregledom daljšega časovnega obdobja jedrskih nesreč in še dodatno razločim kanale, preko katerih jedrske nesreče vplivajo na finančne trge.

Pomembna spoznanja pričujoče disertacije so naslednja. Prvič, najmočnejši učinek izbruha ebole so občutile delnice podjetij, ki poslujejo bližje epicentru izbruha bolezni in so bližje finančnim trgom. Drugič, učinku dogodka sledi povišano zaznano tveganje; to pomeni, da je implicitna volatilnost narasla po izbruhu ebole. Tretjič, učinek dogodka je izrazitejši za majhna podjetja, za bolj volatilne delnice, delnice specifičnih panog in za medijsko izrazito pokrite delnice. Četrtič, ugotovitve, pridobljene iz pregleda širjenja informacij političnih akterjev, kažejo, da je bolj verjetno, da Trump omeni podjetja, ki so mu poznana, s katerimi že ima politični in poslovni odnos, so velika in so prisotna na mednarodnem trgu. Poleg tega ugotovitve kažejo, da lahko Trump s tvitanjem in pojavljanjem v medijih vpliva na stanje delnic podjetja, obseg poslovanja in volatilnost cene delnic. Prav tako je lahko negativni jezikovni ton pri širjenju informacij sprožal negativne donose za omenjena podjetja. Nazadnje analiza nudi dokaze, da vpliv jedrskih nesreč preko »kanala strahu« sproži strah med vlagatelji, ki nato prispeva k padcu cen delnic.

V disertaciji uporabljene metodologije predstavljajo doprinos strokovni literaturi v tem, da zapolnjujejo pomembno vrzel na tem področju ter nudijo pregled aktualnih primerov in razlag finančnih pojavov, ki lahko pomagajo panožnim strokovnjakom, raziskovalcem in širši javnosti bolje razumeti ozadje delovanja finančnih trgov.