



School of Economics and Management

U.S.-China trade conflict: The effect of Donald Trump's tweets on the stock returns of U.S. sectors

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S.G.J. van den Heuvel BSc.
2039584

Supervised by Dr. O.Wilms
Chaired by Dr. J.Gider

School of Economics and Management
Tilburg University

I hereby declare that this dissertation is composed of my own original work, except as indicated otherwise in the text.

Signature: 

Date: 16 / 07 / 2020

Abstract

Donald J. Trump has used his personal Twitter account @realDonaldTrump to cover the U.S.-China trade conflict to an unprecedented extent. Trump's tweets are considered to be informative signals of the future direction of the trade conflict, that may influence investors in the stock market. Studies have identified a relationship between Trump's tweets targeting companies and their daily stock returns. This study aims to build on this knowledge and investigates the effect of Trump's U.S.-China trade-related tweets on the stock returns of U.S. sectors. This study categorises the tweets based on their content (manually) and based on their sentiment by polarity (Sentimentr). Using a short-term event study methodology, this study finds significant abnormal returns for sectors with high exposure to the trade conflict on the event day (Materials, Industrials, Consumer Discretionary, Health Care and Consumer Staples). This study finds no significant abnormal returns for sectors with low exposure to the trade war (Financials, Energy, Utilities and Real Estate). Furthermore, this study finds indications that investors tend to shift their money from cyclical sectors (Materials, IT, Industrials and Consumer Discretionary) towards defensive sectors (Health Care, Consumer Staples and Communication Services) and vice versa, depending on the content and sentiment of Trump's tweets. Generally, the effect of Trump's tweets is temporal rather than lasting.

Keywords: Trump, Twitter, U.S.-China trade, tweets, sectors, stock returns

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This thesis is written during one of the most challenging times of my life and those of many others. The Covid-19 pandemic has taken the lives of many and caused the things we consider as "normal" to cease. On the flip side, this crisis has enabled me to fully focus on writing this dissertation. This thesis marks the end of my period at Tilburg University and marks the end of the first of my two challenges.

I am thankful to my girlfriend who has supported me during my hardships while writing this thesis. Especially, since we have successfully spent the most of our time in lock-down. Furthermore, I want to thank my friends who have encouraged me to study Trump's tweets. I find this topic really intriguing and it was a pleasure to be able to take on a project so actual and novel. I also want to thank my friends and family who have taken the time to read my report and provide me with feedback. Special thanks go to Ole Wilms, who has supervised me during this project.

Contents

Abstract	i
Acknowledgements	iii
1 Introduction	1
1.1 Research Question	3
1.2 Thesis structure	3
2 Theoretical & Literary Overview	4
2.1 Trump and China: Why did it escalate?	4
2.1.1 U.S. and China	4
2.1.2 Trump and China	4
2.2 Trump, Twitter and the link with Financial Markets	5
2.2.1 Trump and Twitter	5
2.2.2 Twitter and Financial Markets	7
2.2.3 Trump's tweets and Financial Markets	9
2.2.4 Trump's trade war tweets and stock returns of U.S. sectors	10
2.2.5 Hypotheses	13
3 Research Methodology	15
3.1 Methodological Approach	15
3.2 Data Collection	16
3.2.1 Tweet Collection	16
3.2.2 Stock Data	17
3.2.3 Sector Exposure Data	18
3.3 Methods of Analysis	18
3.3.1 Classification of Tweets	18
3.3.2 Determination of event days	19

3.3.3	Event & Estimation Window	20
3.3.4	Calculating Abnormal Returns	22
3.3.5	Evaluating Significance	23
3.3.6	Measuring Sector Exposure	25
4	Results	26
4.1	Descriptive Statistics	26
4.2	Content-Based categorisation	27
4.3	Sentiment-Based categorisation	33
4.4	Content-Based vs. Sentiment-Based categorisation	37
4.5	Robustness Checks	38
5	Conclusion & Discussion	40
5.1	Conclusion	40
5.2	Discussion	40
5.2.1	Implications of findings	40
5.2.2	Limitations	41
5.2.3	Suggestions for further research	42
	Bibliography	42
	Appendices	48

List of Tables

2.1	Defensive and Cyclical GICS sectors	13
3.1	Number of securities per GICS code	18
4.1	Descriptives of sample period	26
4.2	Abnormal Returns Content-Based categorisation	32
4.3	Abnormal Returns Sentiment by Polarity categorisation	36
A.1	Event days, Sample tweets and categorisation	50
A.2	Abnormal Returns Content-Based Classification: Robustness Check	51
A.3	Abnormal Returns Sentiment by Polarity Classification: Robustness Check	52
A.4	Robustness Check Pre-Presidency tweet sample	53
A.5	Robust pre-presidency Content-Based categorisation	54
A.6	Robust pre-presidency Sentiment by Polarity categorisation	55

List of Figures

2.1	Trump's followers and Twitter active users	6
2.2	Retweets and Favourites on U.S.-China trade war tweets	7
3.1	Distribution of Trump's tweets on U.S.-China trade war	17
3.2	Timeline of the event study	21
4.1	Escalating: Cyclical vs Defensive sectors	29
4.2	De-escalating: Cyclical vs Defensive sectors	30
4.3	Negative Sentiment: Cyclical vs Defensive sectors	34
4.4	Positive Sentiment: Cyclical vs Defensive sectors	35
4.5	AR manual versus AR software	38
A.1	Exposure GICS sectors to U.S.-China trade war	49

Introduction

"Our next President must stop China's Rip-off of America."

— Donald J. Trump, 09-21-2011, Twitter

As one of the most powerful people in the world, the 45th president of the U.S., Donald John Trump, possesses the power to change the course of the world. His personal Twitter account @realDonaldTrump has been one of his main platforms to share his political ideologies with his followers for years. Often controversial, his Twitter account has grown in popularity and his tweets have been reaching the news more and more frequently. After becoming president, the nature of Trump's tweets has shifted and they have become increasingly political. Even earning him the nickname "Twitter President of the U.S.". Trump's policies on the U.S.-China trade war are heavily criticised domestically and believed to hurt the U.S. economy and its sectors (Erken & Giesbergen, 2019). Throughout the escalation of the U.S.-China trade conflict, his twitter account has provided real-time information on one of the most economically sensitive events of the last decade. Providing an unprecedented insight in the mind of a world leader in conflict.

In the field of finance, there is an overall consensus that Twitter content can influence financial markets and provide relevant information to investors (e.g. Bollen, Mao, & Zeng, 2011). According to the Efficient Market Hypothesis (EMH) presented by Fama (1970), market prices should always reflect new publicly available information and investors are therefore likely to react to news shared on the platform. This study continues to discuss the conditions under which tweets potentially matter in Section 2.2.2.

With the rising popularity of Trump's account, some academics began to study the impact of Trump's tweets on financial markets. Primarily, these studies focused on Trump's tweets targeting specific companies and its relation to their stock returns (e.g. Born, Myers, & Clark, 2017). The study by Born et al. (2017), found significant abnormal returns in the short-term, where the sign of the reaction was determined by the polarity of the tweets. However, there

exists no unanimity in the literature on whether Trump's tweets influence stock returns. Importantly, tweets targeting specific companies are very different compared to tweets about an ongoing trade conflict. Especially, since many of the studies included tweets before Trump was elected president, the appreciation given to his tweets is expected to have increased. To the best of my knowledge, no extensive academic research has been conducted to study the effects of Trump's tweets on sectors or entire markets. U.S. sectors are exposed to the consequences of the trade conflict due to the strong interconnections of both markets (Erken & Giesbergen, 2019). Therefore, this study intends to fill a gap in the literature and study the impact of Trump's U.S.-China related tweets on the stock returns of U.S. sectors. Mainly, the focus of this study is to examine whether stock returns are affected and whether differences between sectors can be observed and explained. This does not only address a gap in the literature, but it also advances the theoretical debate on whether Trump's tweets matter to investors. Generally, this study aims to gain valuable insights into how the content and sentiment of influential individuals on social media during times of conflict can affect investor behaviour and thereby impact the returns of entire sectors. It must be clear that the aim of the study is not to develop an investing strategy but to examine whether investors seem to trade on his tweets.

Although no extensive research has been executed, a report from JPMorganChase (2019) stated that Trump's tweets seem to increasingly move markets. Highlighting, that words like "China", "tariff" or "trade" seemed to be among the most market moving. They even introduced the "Volfefe" index to track the impact of Trump's tweets on the bond market. A study by Benton & Philips (2020), found that Trump's Mexico related tweets increased the volatility of the foreign exchange index. Suggesting, that Trump's tweets acts as informative signals of the future direction of the government and cause investors to anticipate accordingly. The focus of this study is to determine whether a relationship between Trump's tweets and the stock returns of U.S. sectors exists using event study methodology. This study categorises Trump's tweets according to their content (manually) and their polarity (Sentimentr). Subsequently, this study compares the results of both categorisation methods. When a significant relationship between Trump's tweets and the U.S. sectors is found, this study tries to identify differences between sectors and explain the differences according to the literature.

1.1 Research Question

Based on the above discussion, the research question is formulated as follows:

What is the effect of Trump's tweets related to the U.S.-China trade conflict on the stock returns of U.S. sectors?

This study focuses on examining the effects of Trump's tweets on U.S. sectors because this study expects U.S. sectors to react differently to Trump's tweets. Not only do sectors have a different exposure to the trade conflict, sectors also have different inherent levels of risk. In literature, it is common practice to divide sectors and industries according to their riskiness. Typically, academics divide sectors into high-beta and low-beta sectors (e.g. Wilson, 1998). High-beta sectors are more sensitive to changes in the market. Therefore, investing in these sectors is considered more risky but is also supposed to provide higher returns. Low-beta sectors on the other hand are less sensitive to changes in the market. Therefore, investing in these sectors is typically less risky but generally provides lower returns. Practitioners often refer to high-beta sectors as cyclical sectors and to low-beta sectors as defensive sectors. This study expects that Trump's tweets change investors' perceived market risk. As a result, this is expected to change the risk exposure of investors and cause them to shift their investments from and towards cyclical and defensive sectors, based on their interpretation of Trump's tweets. This study continues to discuss this expectation in Section 2.2.4.

1.2 Thesis structure

This study is divided into five chapters: Chapter 2 provides a theoretical and literary overview, Chapter 3 provides a detailed description of the methodology, Chapter 4 presents and discusses the main results, Chapter 5 discusses the main conclusions, implications and limitations of the study, and suggestions for further research.

Theoretical & Literary Overview

The aim of this chapter is to discuss how tweets sent by Donald Trump on the U.S.-China trade conflict can eventually lead to abnormal returns of U.S. sectors by means of a funnel structure. Firstly, this chapter briefly discusses the origination of Trump's attitude towards China. Secondly, it discusses Trump's social media and how information from social media relates to financial markets. Thirdly, it discusses the relationship between Twitter and financial markets and especially the relation of the financial markets to Trump's tweets. Lastly, it discusses through what mechanisms Trump tweets about the trade war can affect the stock returns of U.S. sectors.

2.1 Trump and China: Why did it escalate?

2.1.1 U.S. and China

The U.S. and Chinese economies are more interconnected than ever. The two largest economies of the world, in nominal GDP, are heavily dependent on bilateral trade. U.S. trade with China increased from 125 billion dollars in 2001 to a staggering 700 billion in 2017 (Meltzer & Shenai, 2019). However, frustration in the U.S. has grown over the inherent practices of the Chinese economic model. Their model creates an uneven playing field that favours Chinese companies globally and is perceived by the U.S. as unfair (Meltzer & Shenai, 2019). This dynamic caused the bilateral landscape to shift from cooperation to competition, increasing tensions between both superpowers.

2.1.2 Trump and China

The "unfair" practices of China have been a major source of frustration for Donald Trump, stretching way before he was elected president. His frustration is perfectly illustrated by the following tweet sent by Trump back in 2011: "Our next President must stop China's Rip-off

of America". The main source of his frustration is the rapidly increasing trade deficit of the U.S. in their trade with China. A study by Kashyap & Bothra (2019) shows, that the U.S. trade deficit with China has been rapidly increasing since the start of the 21st century.

Trump's growing frustration over the trade practices of his country has clearly been one of his main motivations to run for president and stop this self-labeled "rip-off" of his country. The renegotiation of trade deals, which Trump often advocated during his presidential campaign, is an integral part of his "America First" policy.

Although there is a discussion among experts on whether trade deficits matter, the concerns of Trump can be justified. The U.S. economy has been the largest and most powerful economy in nominal GDP for years but is quickly being caught by China. Furthermore, an accumulating trade deficit causes a huge public debt and can lead to the stockpiling of dollars. The stockpiling of dollars by the Chinese central bank limits the supply of dollars and puts upward pressure on its value. Ultimately, this reduces the relative value of the yuan, which creates an interesting business climate for cost-cutting, due to reduced labour costs. U.S. companies that want to take advantage, outsource many of their activities to China, causing an increase in unemployment and loss of competitive ability in the U.S (Kashyap & Bothra, 2019).

After the first actions taken by Trump out of protectionism, the situation between the two most powerful nations escalated into a tit-for-tat tariff trade war with a detrimental effect on the domestic markets of both countries (Erken & Giesbergen, 2019). Throughout this trade war, Trump has been using his Twitter account extensively to share the latest developments and opinions on the status of their negotiations.

2.2 Trump, Twitter and the link with Financial Markets

2.2.1 Trump and Twitter

Since its rise over the last decade, social media has been an important platform for Trump to ventilate his opinion and share his political ideologies with the world. During his presidential campaign, Trump's social media platforms played a key role in his marketing strategy and often bypassed editorial media as the direct source of news (Enli, 2017). Out of his social media platforms, his personal Twitter account @realDonaldTrump acts as his main source of communication and has been rapidly growing since becoming president, see Figure 2.1.

With a follower base of approximately 70 million, Trump is not only one of the most followed users on the platform but is also considered as one of the most controversial. Renowned for his feuds on the online platform, Trump's tweets are sentimental and often target individuals,

media, or countries. For example, calling China an enemy of the state on Twitter in 2013: “Our enemy China is illegally buying oil from our enemy Iran”.

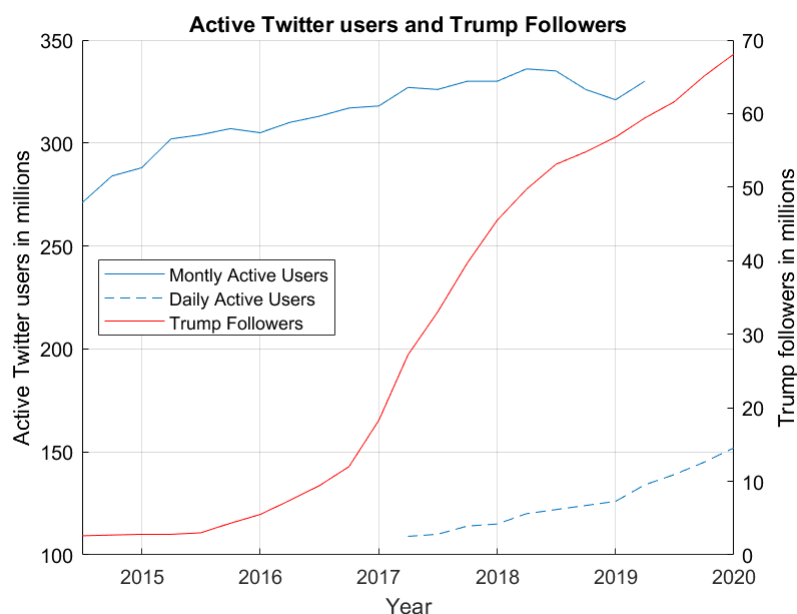


Figure 2.1: Trump's followers and Twitter active users

Established in 2006, Twitter has become one of the main free social media platforms in the world and enables its users to share real-time information. Messages posted in this medium are called “tweets” and originally contained a maximum of 140 characters, this amount was increased to 280 at the end of 2017. These tweets are shared directly with the followers of the user and are stored on the user’s profile. According to the latest data from Statista (2020), Twitter has approximately 330 million monthly active users and 150 million daily active users around the world. Twitter users can share a message posted by another user through a “retweet” and can share their appreciation for a post in the form of a “favourite”. Both retweets and favourites are important measures to determine user engagement and follower interest and preference. For politicians like Trump, retweets are especially important since they are a direct determinant of the tweet’s reach. This is because retweets are directly posted on the user’s feed and shared with the user’s followers, which expands the initial reach of the tweet. The evolution of retweets and favourites received by Trump's tweets on the US-China trade relationship, for sample see Section 3.2.1, show a rapid increase since early 2018. In total, the tweets received approximately 3 million retweets and 13 million favourites by the end of 2019, see Figure 2.2. On average, a tweet received 18 thousand retweets and 82 thousand favourites.

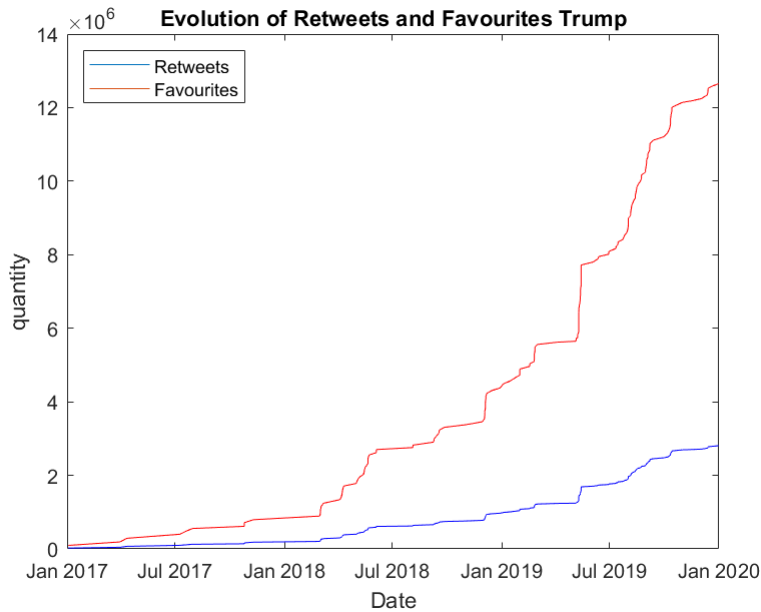


Figure 2.2: Retweets and Favourites on U.S.-China trade war tweets

2.2.2 Twitter and Financial Markets

It is clear that the reach and attention given to Trump's twitter account is huge and continuously growing. Tweets of Trump regularly contain information of economic importance and might be a valuable source for investors. To determine whether Trump's tweets and financial markets are connected, it is important to understand the relationship between news sources and investors. Particularly, how this relationship has changed due to the rise of social media. Nowadays, there is an overall consent in literature that investor behaviour is influenced by both endogenous and exogenous sources of information. Initially, the standard view was that the price of a security was only influenced by information from endogenous sources, indicating a change in the fundamental value of a security. In essence, this assumed that prices were not influenced by any external factor. According to the famous Efficient Market Hypothesis (EMH) by Fama (1970), market prices of securities should always immediately and completely reflect all new publicly available information. However, Fama (1970) only considered information derived from endogenous sources as relevant (e.g. announcements of stock splits). Suggesting that exogenous news factors, such as Twitter, should not matter to investors. A study by Cutler, Poterba, & Summers (1989), was the first to show that exogenous news factors were responsible for at least some of the variation in stock returns and initiated a wave of studies linking exogenous news factors to financial markets.

The rise of social media platforms like Twitter has significantly changed the landscape of knowledge by generating a never-ending continuous stream of real-time publicly available in-

formation. For investors, the proliferating use of social media provides a new opportunity to gather price-sensitive information shared by influential users. These users see social media as a fast and easy way to share information with a large follower base. In particular, this development introduced a new line of research focused on analysing public mood and sentiment on social media as a predictor of stock returns.

It is needless to say that times have changed since the EMH proposed by Fama (1970). A study by Bollen, Mao, & Zeng (2011), even argued that some fundamental assumptions of the EMH are violated in reality and stock prices can be predicted by Twitter mood. The basic assumptions underlying the EMH are that stock prices only react to new information and that stock prices follow a random walk. Bollen et al. (2011) showed, by determining public sentiment from a large collection of tweets, that the returns on the Dow Jones Industrial Average (DJIA) could be very accurately predicted. These findings are substantiated by the study of Zheludev, Smith, & Aste (2014), who found that tweet sentiment leads the financial markets. Their sentiment analysis technique shows that the sentiment of a tweet contains significant information about the future price of the S&P 500. The studies by Ranco, Aleksovski, Caldarelli, Grčar, & Mozetič (2015) and Sprenger, Sandner, Tumasjan, & Welpé (2014) contributed significantly to the field of event study methodology and identified important relationships between tweet characteristics and stock returns. The study by Ranco et al. (2015), found a significant relationship between the tweet sentiment about the DJIA and stock returns during peaks in trade volume. Besides tweet sentiment, Sprenger, Sandner, et al. (2014) categorised a large sample of tweets on the S&P 500 companies based on their content and found a significantly different reaction across the categories. Next to this, Born, Myers, & Clark (2017) states that the assumption of a complete and immediate stock price reaction to an event is unrealistic. They argue that investors, such as noise traders, are irrational and uninformed and may trade on already existing information. This phenomenon might cause a different reaction to the reaction expected by the EMH. Tweet characteristics can be used as a proxy for public mood and can anticipate market reactions. In some cases, a single tweet may disclose new market sensitive information and become the news itself.

For investors, the use of social media as a source of information is generally accepted. A study by Sun, Lachanski, & Fabozzi (2016), showed that a trading strategy based on Twitter data can lead to an attractive Sharpe ratio. However, the sole use of social media as an information source, ignoring traditional sources, might lead to an increase in information asymmetry between investors. A problem that can be reduced by allowing companies to share price sensitive information on Twitter (Blankespoor, Miller, & White, 2013). Eventually, the Securities

and Exchange Commission (SEC) recognised the importance of Twitter as an information intermediary and allowed companies to share corporate news on the platform in 2013.

Generally, there exist two theories that explain how media coverage can influence investor behaviour: the information view and the salience view (Sprenger, Sandner, et al., 2014). Firstly, the information view suggests that media coverage reduces the investors' cost of acquiring information and improves investors' rationality. Hence, allowing the companies to share news on Twitter reduces information asymmetry through reduced cost of acquiring information. Secondly, salience theory suggests that investors can be drawn to specific assets by the media. Human-beings may be drawn towards attention-grabbing information and may forget to care about its validity (Kahneman & Tversky, 1973). This psychological aspect may cause investors to under-react to important information receiving little attention and overreact to highly trending less relevant information.

In sum, it is concluded that there is sufficient evidence to acknowledge the relationship between Twitter content and financial markets.

2.2.3 Trump's tweets and Financial Markets

The reach of Trump on his Twitter platform is rapidly expanding and his tweets are increasingly reaching the news. As one of the most influential and powerful people to ever use the platform Twitter, his messages are undeniably important to investors. Especially, since Trump often targets individual companies and shares important economic information on his Twitter account. Not only is Trump able to directly influence domestic economic policies, he is also able to influence the public mood through his large follower base (Sprenger, Sandner, et al., 2014). As discussed in section 2.2.2, public mood and sentiment can be a good predictor of market prices. According to these findings, there could exist a relationship between sentimental tweets send by Trump and financial markets.

To this moment, the capability of Trump's tweets to move financial markets is not widely studied by academics. Although, there has been plenty of speculation by market watchers that his tweets are indeed able to move markets. For example, a report by JP Morgan Chase stated that Trump's tweets are increasingly moving the markets and that the top-moving words include "China", "tariff" and "trade" (JPMorganChase, 2019). JP Morgan Chase even introduced the "Volfefe" index that tracks the impact of Trump's tweets on the bond market. After plenty of questions by the media, Trump himself stated that he believes his tweets have a significant impact on the stock market (Business Insider, 2019).

One of the first academic efforts to quantify the relationship between Trump's tweets and

financial markets was the effort from Born et al. (2017). The first line of research primarily focused on tweets of Trump targeting individual companies and their stock returns. Born et al. (2017) found that the polarity of Trump's tweets caused a similar short-term reaction in the companies stock returns. A significant relationship was also found for the stock returns of targeted media companies (Ajjoub, Walker, & Zhao, 2018). In contrast, Juma'h & Alnsour (2018) did not find any significant relationship between Trump's tweets and targeted companies stock returns. Another interesting study to mention is the study by Dinh, Kopf, & Seitz (2017), who found that tweets from the famous hedge fund activist Carl Icahn that targeted companies, led to significant abnormal returns in the short term.

During his presidency, Trump's tweets became increasingly political, often addressing issues of macro-economical importance. This initiated a shift in studies not only focusing on individual company returns, but studying the effects on financial markets and foreign exchange markets as a whole. An example is the study by Colonescu (2018), who found a significant short term relationship between Trump's tweets and the DJIA. Interestingly, he build on the findings of the study by Bollen et al. (2011), as discussed in Section 2.2.2. The latest effort was the work by Benton & Philips (2020), who argued that while it is known that investors react to new information about the future policy direction of governments, information can also arise from the likely direction of the government and cause investors to react. Benton & Philips (2020) argued that Trump's tweets are a measure of likely direction, although his real policy views are unknown, they stated that these information would matter to financial markets as well. They found a significant increase in the volatility of the Mexican peso and concluded that Trump's tweets act as a signal that causes investors to react.

I share the view presented by Benton & Philips (2020), Trump's tweets can be seen as signals that may disclose some of the future government policies. Many studies suggested and found that a relationship between Trump's tweet and the financial market exists. Due to the increasing attention given to Trump's twitter account and the economic relevant information shared on the platform, the relationship is expected to be even stronger now.

2.2.4 Trump's trade war tweets and stock returns of U.S. sectors

In the previous sections, this study has briefly touched upon the importance of the U.S.-China trade relationship. Their markets are more interconnected than ever and many U.S. companies rely heavily on the Chinese economy. The report from JPMorganChase (2019) suggested that terms like "China", "tariff" and "trade" were the most market moving words in Trump tweets. Academics have found evidence that Trump's tweets are indeed able to influence the financial

markets. However, to the best of my knowledge, no academic effort has been made to study the effects of Trump's tweets about the U.S.-China trade war on the stock returns of U.S. sectors. Therefore, this study could provide valuable insights in how the social media strategy of influential individuals during times of conflict can impact financial markets. Especially, when this influential user is the president of the U.S., a key player in this conflict. In the field of finance, this study could help to understand the impact of Trump's Twitter account on financial markets, which could provide helpful knowledge to market analysts and investors in the future. Overall, this study helps to advance the theoretical debate on whether his tweets are relevant to financial markets.

The policies of Trump towards China have encountered major criticism from market watchers in the U.S. Many of the U.S. sectors are suffering from the trade war and are in constant fear of retaliation by China (Erken & Giesbergen, 2019). The fear of an escalating trade war is logical. Many U.S. sectors are heavily exposed to the trade war due to the interconnections between both markets. U.S. sectors import and export many intermediary goods from and towards China and fear a disruption of their supply chains (Erken & Giesbergen, 2019). Furthermore, both tariffs imposed by the U.S. and China cost U.S. companies billions of dollars and reduces their margins. The longer these tariffs last, the more money will be lost. The paper of Huang, Lin, Liu, & Tang (2018) found that the exposure of a firm to the trade war is a determinant of their reaction to tariff announcements. They state that firms with higher exposure to the trade conflict are likely to suffer most. The urgency of the conflict was underlined by the study of Steinbock (2018), suggesting that this trade war could lead to a lasting global recession.

Trump's tweets on this trade war are therefore expected to be very sensitive and important to investors. Due to his nature, Trump has the tendency to be very sentimental and unpredictable, which adds to the uncertainty in the financial market. For investors, this uncertainty leads to an increase in perceived risk associated with their investment. When perceived risk increases, investors often flee towards "safe heaven" assets, such as gold, bonds or defensive stocks (Rolph, 2017). This behaviour is linked to "risk-on risk-off" (RoRo) theory (Papenbrock & Schwendner, 2015). This theory states that investors' appetite for risk can change according to their perceived market risk. RoRo theory suggests that when perceived market risk is high, risk is "off" and investors engage in low-risk investments. When perceived market risk is low, risk is "on" and investors engage in high-risk investments.

In the field of finance, research into the relationship between risk/return levels and the nature of the industry is longstanding. A study by King (1966), found that the differences in the level of risk and return are sufficient to attribute these differences to the industry effect. Furthermore,

this study concluded that the movement of a group of securities can be broken down into industry components. As a result of this notion, it makes sense to divide industries or sectors based on their risk. Generally, academics categorise sectors into high-beta sectors and low-beta sectors (Wilson, 1998). Later academic studies, such as Asinas (2018), have also adopted the categorisation used by practitioners, who often divide the sectors into cyclical and defensive sectors. The definitions of both methods are highly related and the two methods can be used interchangeably. Alike high-beta sectors, cyclical sectors are sectors that follow the trend of the overall economy and tend to perform well in a good economy. Because cyclical sectors are very sensitive to changes in the market, they are generally riskier and are supposed to provide a higher return. Alike low-beta sectors and contrary to cyclical sectors, non-cyclical sectors or defensive sectors tend to be more resilient when the economy is down. Because defensive sectors are less sensitive to changes in the market, they are generally less risky and are supposed to provide lower returns. The sectors are categorised according to the report by MSCI (2016), see Table 2.1.

The relationship between beta and returns is widely studied by academics. The study by Fama & French (1992), showed that the returns are not explained by levels of beta, but rather by book-to-market equity (B/MV). Firms with a low B/MV are referred to as growth stocks and firms with high B/MV are referred to as value stocks. This finding by Fama and French does not imply that beta and B/MV are unrelated. A study by Capaul, Rowley, & Sharpe (1993), found that firms with a high B/MV typically have a lower beta, and firms with a low B/MV tend to have a higher beta. Additionally, they found that portfolios of high B/MV stocks provided returns higher than portfolios of low B/MV stocks. This finding suggests that investors use other risk measures than beta. Contrary to the previous findings, Harris & Marston (1994) found that this inverse relationship is attributable to the failure to account for growth. After they controlled for growth, beta and B/MV showed a significant positive relationship. This finding is in line with pricing models arguing that investors are indeed averse to beta risk.

Based on the aforementioned notions, it is expected that when Trump escalates the situation on Twitter, perceived risk rises, and investors shift away from cyclical sectors towards defensive sectors. When Trump de-escalates the situation it is expected that perceived risk declines, and investors return to the more profitable cyclical sectors.

Table 2.1: Defensive and Cyclical GICS sectors

GICS Sector Code	Sector	Type
10	Energy	Defensive
15	Materials	Cyclical
20	Industrials	Cyclical
25	Consumer Discretionary	Cyclical
30	Consumer Staples	Defensive
35	Health Care	Defensive
40	Financials	Cyclical
45	Information Technology	Cyclical
50	Communication Services	Defensive
55	Utilities	Defensive
60	Real Estate	Defensive

Note: This table shows the division of the GICS sectors into cyclical and defensive sectors based on MSCI (2016).

2.2.5 Hypotheses

In the previous sections, this study argued that the appreciation given to Trump's tweets is likely to have grown. Furthermore, the study by JPMorganChase (2019) found that Trump's tweets related to the U.S.-China trade conflict seemed to be moving the markets. By answering Hypothesis 1, this study intends to learn whether his U.S.-China related tweets are indeed able to affect the stock returns of U.S. sectors. With this knowledge, this study aims to provide more insights into how the social media of influential users can impact financial markets. This study expects to find at least some significant reactions to Trump's tweets on the event day.

Hypothesis 1 (H1): *Trump's tweets on the U.S.-China trade conflict significantly impact U.S. sector stock returns*

The study by Erken & Giesbergen (2019) found that U.S. sectors are exposed to the U.S.-China trade conflict. However, some sectors are more heavily exposed than others. According to Huang et al. (2018) firms with higher exposure to the trade war are more likely to suffer. Therefore, this study expects that sectors with high exposure significantly react to Trump's tweets. Answering Hypothesis 2 is important because it helps to explain possible differences among sectors.

Hypothesis 2 (H2): *Trump's tweets on the U.S.-China trade conflict only significantly impact sectors with high exposure to the U.S.-China trade war*

Based on the work by Sprenger, Sandner, et al. (2014), financial markets are known to react according to tweet content. This study expects that Trump's tweets change investors' per-

ceived market risk. Therefore, this study expects that the content of Trump's tweets leads to investors shifting their investments from and towards cyclical and defensive sectors. Answering Hypotheses 3 & 4 helps to understand whether investors react according to the content of Trump's tweets.

Hypothesis 3 (H3): *Trump's escalating (de-escalating) tweets on the U.S.-China trade conflict will lead to a positive (negative) stock reaction for defensive sectors*

Hypothesis 4 (H4): *Trump's escalating (de-escalating) tweets on the U.S.-China trade conflict will lead to a negative (positive) stock reaction for cyclical sectors*

Based on the work by Colonescu (2018), financial markets are known to react based on tweet sentiment. This study expects that Trump's tweets change investors' perceived market risk. Therefore, this study expects that the sentiment of Trump's tweets leads to investors shifting their investments from and towards cyclical and defensive sectors. Answering Hypotheses 5 & 6 helps to understand whether investors react according to the sentiment of Trump's tweets.

Hypothesis 5 (H5): *Trump's negative (positive) sentiment tweets on the U.S.-China trade conflict will lead to a positive (negative) stock reaction for defensive sectors*

Hypothesis 6 (H6): *Trump's negative (positive) sentiment tweets on the U.S.-China trade conflict will lead to a negative (positive) stock reaction for cyclical sectors*

In line with the study of Born et al. (2017), this study expects that the effects of Trump's tweets are on average temporal rather than lasting and that the effect is quickly offset after the event day. Answering Hypothesis 7 is important because it helps to understand which type of investors typically react to Trump's tweets.

Hypothesis 7 (H7): *The effects of Trump's tweets are temporal rather than lasting*

Research Methodology

This chapter discusses the methodology used to answer the research question. Firstly, this chapter discusses the main methodological approach. Secondly, this chapter discusses the methods of data collection. Thirdly, this chapter discusses the methods of analysis, which obstacles were faced and how they were overcome, and the tools and materials used in this study. Throughout the chapter, the applied methods are evaluated and justified.

3.1 Methodological Approach

This research aims to quantify the impact of Trump's U.S.-China trade related tweets on the daily stock returns of different U.S. sectors by conducting a short-term event study. Event studies have been used for decades to study the effects of an economically relevant event on the value of a firm. In finance research, event studies have been successfully used for many different applications and are a standard for evaluating the impact of event news on stock prices (Sprenger, Sandner, et al., 2014). The underlying assumptions when conducting an event study are that markets are efficient and prices of a security immediately reflect new information, the event itself is unanticipated and there are no confounding events in the event window (Brown & Warner, 1980).

This study assumes market efficiency in the semi-strong form, which states that prices are adjusted until the market fully reflects all publicly available information (Fama, 1970). This definition of efficiency can only hold when information is easily accessible and simultaneously shared. These conditions are satisfied by tweets sent by Trump, since the tweets on the U.S.-China trade relationship are new, economically relevant and accessible to every market participant. The degree to which the information of the tweets is new to the market is not easily determined, but can be encompassed by observing days before the event and carefully filtering the tweets, see Section 3.2. However, given the functionality of the platform Twitter and the unpredictable nature of Trump it can be assumed that information leakage is minimal.

Although some noise is unavoidable due to the unstructured nature of tweets, confounding events are strictly controlled and lead to the removal of tweets. The probability of having a confounding event is also reduced by conducting a short-term event study, with respect to a long-term event study. Based on the above arguments, it is believed that a short-term event study can be used as a valid and rigorous approach to answer the research question.

3.2 Data Collection

3.2.1 Tweet Collection

This study uses a collection of tweets send by the 45th president of the U.S. Donald John Trump on his official Twitter account @realDonaldTrump. The collection contains tweets on the U.S.-China trade relationship send after his election on November 8, 2016 until the completion of the Phase One deal in December 2019. An explanation for considering his post-electoral tweets is that the dynamics, concerning his pre-electoral period, are likely to have changed. As president, Trump possesses the power to influence politics and enact propositions made on Twitter, potentially affecting U.S. sectors. To an investor, this has likely changed the appreciation given to his tweets.

Tweets containing the word "China" in combination with the words: "trade", "tariff", "deal", "negotiation" were extracted from TrumpTwitterArchive (2020). In addition, retweets, reactions to tweets of other users, tweets with a clear reaction on another news event happening the same day and tweets containing keywords in another context were removed from the sample to avoid contamination. To ensure validity of the sample tweet, the timestamps, retweets and favourites of the database have been compared to his original account. The final collection consists out of 168 tweets, for their distribution over time, see Figure 3.1. The figure shows an increase in tweets during the year 2019.

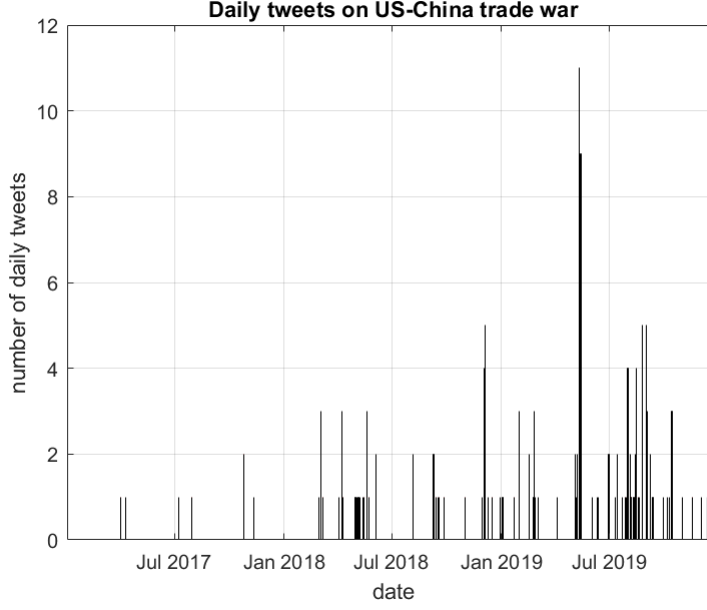


Figure 3.1: Distribution of Trump's tweets on U.S.-China trade war

3.2.2 Stock Data

Daily stock returns were obtained for all 505 large-cap stocks of the S&P 500 from the WRDS CRSP database between January 1, 2011 and December 31, 2019. The CRSP database is updated annually and has no daily stock returns of stocks available after December 31, 2019. Data was retrieved from 2011 to ensure plenty of data was available to estimate parameters. Returns were measured as the returns without dividends of the daily closing prices. Furthermore, variables such as, number of shares outstanding and share price were extracted from the database. Subsequently, the S&P 500 constituents were divided into 11 different sectors according to the Global Industry Classification System (GICS), see Table 3.1

To measure the effect of Trump's tweets on sectors, the stock returns of the individual constituents were used to create a value-weighted sector portfolio for every sector with the help of the statistical package Matlab. This study defines ω_{ikt} as the weight of security i belonging to sector k at time t , O_{ikt} as the number of shares outstanding, P_{ikt} as the stock price and N_k as the number of securities belonging to sector k .

$$\omega_{ikt} = \frac{P_{ikt}O_{ikt}}{\sum_{i=1}^{N_k} P_{ikt}O_{ikt}} \quad (3.1)$$

Finally, using the weights obtained from equation (3.1), the return R on the sector portfolio at time t is calculated.

$$R_{kt} = \sum_{i=1}^{N_k} \omega_{ikt} R_{ikt} \quad (3.2)$$

Table 3.1: Number of securities per GICS code

GICS Sector Code	Sector	# Securities
10	Energy	31
15	Materials	25
20	Industrials	67
25	Consumer Discretionary	82
30	Consumer Staples	34
35	Health Care	61
40	Financials	69
45	Information Technology	72
50	Communication Services	3
55	Utilities	28
60	Real Estate	33

Note: This table shows the number of securities per GICS code

3.2.3 Sector Exposure Data

Sector exposure was measured based on export exposure and import exposure. Data on export exposure, proxied by revenue exposure to China, is retrieved from CNBC (2019), MSCI Research (2019) and the GeoRev database from DataStream. Data obtained from DataStream included the geographical revenue for every S&P500 constituent over the year 2016, the year before the analysis. Import exposure was measured according to the free database of Hoberg & Moon, which is a database that uses an algorithm to read the 10-K's of publicly traded U.S. companies for disclosure of their international activities. The variable offshore input measures the amount of times a company mentions buying products from a given country. The database was filtered for companies mentioning buying products from China between 2013 and 2017.

3.3 Methods of Analysis

3.3.1 Classification of Tweets

The individual tweets were classified to assess the impact of Trump's tweets on the different U.S. sectors. Tweets were classified both on their content, based on Sprenger, Tumasjan, et al. (2014) and their sentiment, based on Colonescu (2018). The outcomes of these methodologies were subsequently compared.

The content of Trump's tweets on the U.S.-China trade relationship was manually classified as either "escalating" or "de-escalating". Within the course of the tensions between the two countries, a clear distinction is observed in the tweets sent by Trump. On the one hand, this

study observes tweets that threaten to impose or raise tariffs such as: "...during the talks the U.S. will start on September 1st putting a small additional Tariff of 10% on the remaining 300 Billion Dollars of goods and products coming from China into our Country. This does not include the 250 Billion Dollars already Tariffed at 25%". Tweets of this kind, or tweets that show a negative attitude towards China, and others that are expected to push the situation away from a trade deal are marked "escalating". On the other hand, we observe a series of tweets that are trying to achieve the opposite and seem to be an attempt to unify the two countries and are expected to bring the deal closer such as: "President Xi and I have a very strong and personal relationship. He and I are the only two people that can bring about massive and very positive change on trade and far beyond between our two great Nations". Tweets that have a positive attitude towards China, the deal, removing tariffs, or upcoming talks are marked "de-escalating".

Next to the manual classification of tweets, the tweets are classified according to their sentiment score by polarity, either "positive" or "negative", using the "Sentimentr" package of the statistical program R. Several studies have shown dependence between tweet sentiment and abnormal returns (e.g. Ranco et al., 2015). Moreover, software packages have been used to quantify tweet sentiment before (e.g. Colonescu, 2018). Simplified, Sentimentr uses an augmented dictionary method. The algorithm assigns a polarity to a sentence by determining the sentiment word for word using a sentiment dictionary. The algorithm then groups the text into sentences and determines the average. The values can range between -1.0 and +1.0. For example, tweets like "China is intent on continuing to receive the hundreds of Billions of Dollars they have been taking from the U.S. with unfair trade practices and currency manipulation. So one-sided it should have been stopped many years ago!" received a "negative" sentiment score of -0.47. While tweets like "Getting VERY close to a BIG DEAL with China. They want it and so do we!" received a "positive" sentiment score of 0.1.

3.3.2 Determination of event days

Determining the correct event day is a crucial step for a rigorous approach. In this study, the event day is defined as the first trading day after the tweet went public, where the tweets are treated as the events. The exact moment a tweet is posted is accurately captured in the timestamp of the tweet. However, the timestamps extracted from the database were converted from the Greenwich Mean Time zone (GMT) to Eastern Standard Time (EST), to represent the timezone of the U.S. major stock exchanges. When the timestamp of a tweet is outside of trading hours, the tweet is analysed on the subsequent trading day.

After obtaining the event days of the individual tweets, we observe multiple tweets with the same event days or subsequent event days, caused by Trump tweeting in bursts. This is partly explained by the fact that tweets have a limited amount of characters, which causes Trump to convey his messages over multiple tweets. These tweets are treated as one, but still do not solve the obstacle of many subsequent event days. This obstacle is overcome with the help of classification, see Section 3.3.1.

One or multiple tweets of the same category with the same or subsequent event days are considered a group, placing the event day of the group on the event day of the first tweet. Trump's tweets that are close together tend to convey a very similar message and are in the same category. A possible explanation for this is that Trump's mood changes with the state of the trade deal, which typically does not change daily. By using this grouping method, the effect of a Trump tweet can be observed over multiple days, there are no tweets before the event day and we can assume independence among groups. This assumption is reasonable since the effects of his tweets are known to be short-lived (Born et al., 2017). When the message is not consistent among subsequent tweets, they are removed from the sample. This method led to a total of 40 groups. Manual classification resulted in 19 "escalating" and 21 "de-escalating" groups of tweets. For the classification of sentiment, the scores obtained for every tweet of a group were averaged based on the average sentiment method (Colonescu, 2018). Based on the methodology of Sprenger, Sandner, et al. (2014) the groups were divided into categories, for this study using two categories: "positive" or "negative". When the average sentiment of a group was equal or bigger than 0, the group was classified as "positive", others were classified "negative". This method resulted in 11 "negative" groups and 29 "positive" groups. For all event days and categorisation, see Table A.1 in the appendix.

3.3.3 Event & Estimation Window

This study aims to capture the immediate effect of Trump's tweets. Therefore, using a short event window is the most logical option. A short event window also reduces the possibility of having confounding events compared to longer event windows (McWilliams & Siegel, 1997). In addition, Brown & Warner (1980) states that the accuracy of the tests decreases with the length of the event window.

The event window of $[-2,2]$ used in this study has a length L_2 of five trading days and is consistent with the event window used by Juma'h & Alnsour (2018). Observing days around the event helps to reduce some of the challenges discussed in Section 3.1. For example, observing two days before the event helps to assess the newness of information (MacKinlay,

1997). Moreover, observing two days after the event helps to understand the tenacity of the effect. The days after the event day can, by construction of the groups explained in Section 3.3.2, include some tweets. Nevertheless, the focus will be on the event day, as most event studies find the major price reaction on the arrival day of new information (Schmitz, 2007).

The event windows of the groups are non-overlapping and assumed to be independent.

The estimation window is placed before the first group and has a length L_1 of 250 trading days. The choice to place the estimation window before the first group of events can be explained by the fact that groups of tweets can follow in rapid succession and plenty of data is available before the first event. The location of the estimation window is a trade-off between avoiding contamination and the risk of a potential misestimation of parameters due to a changing relationship. On the one hand, an estimation window that overlaps other event windows would suffer from contamination caused by the events and can lead to the misspecification of parameters (MacKinlay, 1997). Placing the estimation window far away from the event window is often used to reduce the effect of the event on the estimation window as much as possible (e.g. Sprenger, Sandner, et al., 2014). Therefore, by placing the estimation window before the first group, the market has not been able to anticipate any tweets. On the other hand, the effect of the changing relationship between the indices and market is expected to be minor for this study by considering several things. Firstly, the sector portfolios are, in most cases, less volatile than individual stocks and their parameters are less likely to change over time (Herron, Lavin, Cram, & Silver, 1999). Secondly, Kothari & Warner (1985) find that misestimation of the beta tends to produce smaller errors in short-term event studies and that it is unlikely that the relationship changes inside the event window. Thirdly, a considerably long estimation window is chosen to match the long time between estimation window and events. The timeline of the event study is depicted in Figure 3.2.

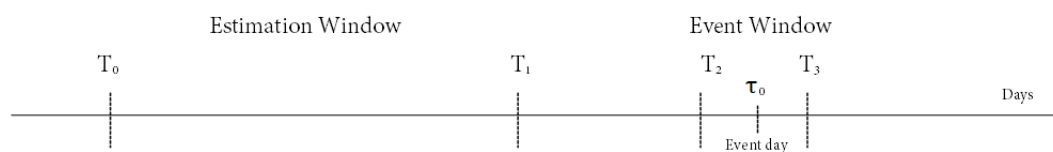


Figure 3.2: Timeline of the event study

3.3.4 Calculating Abnormal Returns

The calculations of the abnormal returns are based on the methodologies presented by MacKinlay (1997) and Brown & Warner (1985). The reaction of the security to an event is measured by identifying whether the return around an event has been abnormal (Brown & Warner, 1980). The only way to determine whether the returns after an event were abnormal, is to compare them with the returns had the event not taken place. These so called "counterfactual" returns are estimated with the help of a benchmark model. For this event study the most common benchmark model, the Market Model (MM), is used. The MM is a statistical model which links the return of the security and the market portfolio (MacKinlay, 1997). Brown & Warner (1985), find that methodologies based on the MM are both well-specified and relatively powerful under a wide range of conditions. Furthermore, MacKinlay (1997) adds that in multifactor models, factors other than the market factor add relatively low explanatory power. Hence, the MM is a reliable option. The S&P composite index is used as the market model, because it has the highest correlation with the sector portfolios. The calculations are performed using Matlab. The parameters of the market model were estimated by OLS regression for every stock portfolio k at time t against the returns on the S&P 500 composite index m at time t given by:

$$R_{kt} = \alpha_k + \beta_k R_{mt} + \epsilon_{kt} \quad (3.3)$$

$$\text{var}(\epsilon_{kt}) = \sigma_{\epsilon_k}^2 \quad E(\epsilon_{kt}) = 0$$

The estimated parameters are used to calculate the abnormal returns AR of the portfolio at event time τ by the following model:

$$AR_{k\tau} = R_{k\tau} - (\hat{\alpha}_k + \hat{\beta}_k R_{m\tau}) \quad (3.4)$$

$$\sigma_{AR_{k\tau}}^2 = \sigma_{\epsilon_k}^2 + \frac{1}{L_1} \left(1 + \frac{(R_{m\tau} - \hat{\mu}_m)^2}{\hat{\sigma}_m^2} \right) \quad (3.5)$$

The second-term of the variance, see equation (3.5), is assumed to converge to zero as the length of the estimation window L_1 is large. Subsequently, the average abnormal return AAR is calculated by aggregating the AR 's over the cross-section of events belonging to the same category J , see Section 3.3.1 for the categories. By taking the average over multiple similar events it is expected that noise caused by unrelated factors cancels out on average. This study defines N_J as the number of events belonging to category J , τ as the event time and j to illustrate the AR of the j^{th} event belonging to category J .

$$AAR_{k\tau}^J = \frac{1}{N_J} \sum_{j=1}^{N_J} AR_{k\tau}^j \quad (3.6)$$

$$\sigma_{AAR_{k\tau}}^2 = \frac{1}{N_J - 1} \sum_{j=1}^{N_J} (AR_{k\tau}^j - AAR_{k\tau}^J)^2 \quad (3.7)$$

The AAR are useful to evaluate the impact of the tweets at one moment in time for a specific category of tweets, aggregating over time is useful to trace the reaction over a longer period. The cumulative abnormal returns CAR are calculated according to equation (3.8).

$$CAR_k = \sum_{t=\tau-2}^{t=\tau+2} AR_{kt} \quad (3.8)$$

$$\sigma_{CAR_k}^2 = \sqrt{L_2} \sigma_{\epsilon_k}^2 \quad (3.9)$$

The CAR 's are also aggregated over event type to see how the sector react on average to an event type over time. The cumulative average abnormal returns $CAAR$ are calculated according to equation (3.10).

$$CAAR_k^J = \sum_{\tau=\tau-2}^{\tau=\tau+2} AAR_{k\tau}^J \quad (3.10)$$

$$\sigma_{CAAR_k^J}^2 = \frac{1}{N_J - 1} \sum_{j=1}^{N_J} (CAR_k^j - CAAR_k^J)^2 \quad (3.11)$$

The standard errors are expected to be consistent since it was assumed that there is no dependency between groups of tweets, see Section 3.3.2.

3.3.5 Evaluating Significance

To obtain inference on the significance of the abnormal returns calculated in Section 3.3.4, two significance tests are conducted. Statistical tests are distributed into two groups: parametric and non-parametric tests. The main difference between the two is that the former assumes normality of the abnormal returns and the latter does not rely on any of these assumptions. The two tests used in this study are the commonly used t-test and the rank test as proposed by Corrado (1989). It is not uncommon that non-parametric tests are used to complement parametric test in cases of few events and possible outliers (e.g. Schipper & Smith, 1983). Due to the limited amount of events per category in this study, the statistics may be sensitive to outliers and randomness. Thus, complementing the t-test with a rank test is likely to improve the robustness of the study.

Brown & Warner (1985) addresses that daily returns and excess returns of individual securities often substantially depart from normality, possibly violating the critical assumption of parametric tests. However, the abnormal returns of the sector portfolios -comprised of multiple individual securities- tend to converge to normality based on the Central Limit Theorem and

do not violate this assumption. Using the outcomes of equations (3.4) to (3.11) the t-statistics were computed accordingly:

$$t_{AR_{k\tau}} = \frac{AR_{k\tau}}{\sigma_{\epsilon_k}} \quad (3.12)$$

$$t_{AAR_{k\tau}^J} = \sqrt{N_J} \frac{AAR_{k\tau}^J}{\sigma_{AAR_{k\tau}^J}} \quad (3.13)$$

$$t_{CAR_k} = \frac{CAR_k}{\sigma_{CAR_k}} \quad (3.14)$$

$$t_{CAAR_k^J} = \sqrt{N_J} \frac{CAAR_k^J}{\sigma_{CAAR_k^J}} \quad (3.15)$$

The rank test as proposed by Corrado (1989), transforms the abnormal returns into ranks and standardizes them by dividing the ranks with the sum of the non-missing items M_i in the estimation window and the event window of an event i plus one.

$$U_{it} = \frac{rank(AR_{kt})}{M_i + L_2 + 1} \quad (3.16)$$

Firstly, the average standardized rank $\bar{U}_t$ is calculated, which can be done for all events belonging to category J . Secondly, the variance across ranks is computed. Where N_t is defined as the number of non-missing returns across events.

$$\bar{U}_t = \sum_{i=1}^{N_t} U_{it} \quad (3.17)$$

$$\sigma_{\bar{U}_t}^2 = \frac{1}{L_1 + L_2} \sum_{T_0}^{T_3} \frac{N_t}{N} (\bar{U}_t - 0.5)^2 \quad (3.18)$$

The results from equations (3.16) to (3.18) are used to compute the test statistics for the AAR and CAAR.

$$t_{rank,AAR} = \sqrt{N_J} \frac{(\bar{U}_t - 0.5)}{\sigma_{\bar{U}_t}} \quad (3.19)$$

The test statistic for the CAAR is based on the work of Campbell & Wasley (1996) for measuring multiday event periods. Where $\bar{U}_\tau$ is the average rank across events in the event window.

$$t_{rank,CAAR} = \sqrt{L_2} \left(\sqrt{N_J} \frac{(\bar{U}_\tau - 0.5)}{\sigma_{\bar{U}_t}} \right) \quad (3.20)$$

3.3.6 Measuring Sector Exposure

The revenue exposure was measured according to three sources, see Section 3.2.3. The data from the websites provided a percentage of revenue exposure to China for every GICS sector. The data from GeoRev was filtered for firms reporting revenue from China, divided into GICS sectors, and averaged to obtain the average revenues from China. Subsequently, all three measures are ranked based on low to high exposure, averaged, and ranked again to obtain a crude hierarchy of sector export exposure.

Measuring import exposure is hard since the numbers are often very opaque and undisclosed. This study uses a methodology based on the method used by Huang et al. (2018) to obtain a crude measure of import exposure. The data obtained from the Hoberg & Moon database is searched on the presence of S&P 500 constituents i belonging to sector k . The number of firms in a sector is defined by N_k . The variable δ_{ik} is defined as a binary variable with $\delta_{ik} \in \{0, 1\}$. When a constituent has mentioned buying a product from China the binary value is set equal to 1 and zero otherwise. The crude measure Θ_k^{China} of export exposure for every sector is given by:

$$\Theta_k^{China} = \frac{\sum_{i=1}^{N_k} \delta_{ik}}{N_k} \quad (3.21)$$

Lastly, the two measures are combined to proxy the exposure, see Figure A.1 in the appendix.

Results

In this chapter, the results of the study are discussed. Firstly, this study provides some descriptive statistics of the different sectors. Secondly, the chapter discusses the outcomes of the event study based on their classifications. Thirdly, the chapter compares the two categorisation methods and their outcomes. Lastly, this chapter discusses the efforts to check the robustness of the outcomes.

4.1 Descriptive Statistics

Table 4.1: Descriptives of sample period

Sector	β	mean Return	std Return	mean MarketCap \$	std MarketCap \$
Materials	1.15	0.0004	0.0097	4.49e+11	1.02e+11
IT	1.08	0.0010	0.0110	4.04e+12	1.56e+12
Health Care	0.94	0.0006	0.0086	2.51e+12	7.23e+11
Consumer Staples	0.63	0.0003	0.0072	1.76e+12	2.92e+11
Industrials	1.07	0.0005	0.0092	1.84e+12	3.90e+11
Consumer Discretionary	0.98	0.0007	0.0089	2.35e+12	6.92e+11
Communication Services	0.54	0.0001	0.0104	4.06e+11	6.73e+10
Energy	1.18	0.0002	0.0118	1.35e+12	1.46e+11
Financials	1.45	0.0007	0.0108	2.31e+12	5.59e+11
Utilities	0.40	0.0004	0.0084	5.61e+11	1.28e+11
Real Estate	0.40	0.0004	0.0077	6.67e+11	1.55e+11
S&P 500	1.00	0.0005	0.0078	1.82e+13	2.73e+12

Note: This table shows descriptives over sample period of tweets 2017-2019, β are inside estimation window and defensive sectors are in bold font

The descriptive statistics of the different sectors were summarized, see Table 4.1. The descriptive table shows the estimated beta's for every sector in the estimation window. This study found that the defensive sectors were the sectors with the lowest beta on average. The average and standard deviation of the daily returns and market capitalization were computed

over the sample period of tweets. Therefore, the descriptive statistics indicate the sector size and performance during the period of Trump's tweets. The average daily return on the S&P 500 index was approximately 0.05% and had a standard deviation of 0.78%. The average market capitalization of the S&P 500 was 18.2 trillion U.S. dollars.

4.2 Content-Based categorisation

In this section, the results of the manual categorisation based on tweet content are highlighted. Table 4.2, shows the average abnormal returns of the sector portfolio during the event window aggregated over the categories, as specified in Section 3.3.1.

Firstly, this study discusses the reaction to the main focus, the event day itself. The results support that the reaction of the market primarily occurs on the event day. Additionally, different reactions to the categories are observed, which is in line with existing literature (Ajjoub et al., 2018).

On the event day, de-escalating tweets show a statistically significant positive reaction for two sectors: Materials and Consumer Discretionary. Economically, the results suggest that a de-escalating tweet leads to an abnormal return of respectively 0.31% and 0.16% on the event day. When multiplied by the mean market cap of both sectors, this results in an approximate increase of respectively 1.4 billion and 3.7 billion dollars in market capitalization on that day. These results support Hypothesis 1, that Trump's tweets significantly impact the stock returns of sectors. Although there is no significant effect observed for the other sectors, this study detected both positive (IT) as well as negative reactions (Health Care, Consumer Staples) to Trump's de-escalating tweets. On the event day, escalating tweets showed a statistically significant positive reaction for two sectors: Health Care and Consumer Staples. Respectively, 0.21% and 0.26% average abnormal returns. In contrast, a statistically significant negative reaction is found for the Industrials sector of -0.23%. Interestingly, the sectors that are close to but not statistically significant still seem to react differently. For example, a negative reaction (Materials, IT, Consumer Discretionary) is found as well as a positive reaction (Communication Services). These findings suggest that defensive and cyclical sectors might indeed react differently. No significant results on the event day are found for sectors such as Energy, Financials, Utilities, and Real Estate, which is in line with the results from sector exposure, see Figure A.1. It is intuitive that sectors with low exposure to the U.S.-China trade war do not significantly react to Trump's tweets, which is in line with Hypothesis 2.

Secondly, the surrounding days of the event study are discussed. On the days before the event, some significant abnormal returns are identified. Generally, these results are somewhat

unexpected since there are no tweets present before the event day by construction. These results could be explained by information leakage, although unlikely given the nature of Trump, investors might have information that an announcement from Trump is nearing. For example, the statistically significant negative reaction of the Materials sector prior to an escalating tweet. This negative reaction is followed by another negative reaction on the event day itself, which might be an indication that some investors anticipated the escalating nature of Trump's tweets and others followed. Another explanation for the significant results, such as for the Financials sector, is the limited amount of events. Sometimes, by coincidence, the sample of a sector before and after the event day might include predominantly negative or positive abnormal returns. This can eventually lead to a higher chance of having a Type-I error. In this case, the result is likely to be a Type-I error since the result was not consistent among the other sectors and the sector itself also did not react on the event day. Importantly, this requires the other results to be interpreted with some care. On the days after the event, by construction, some tweets were present, which could be a reason for significance. In addition, noise trading could be a reason for significant returns after the event day. Tweets from Trump are often picked up by the news at a later moment and may cause investors to react later, which would be inconsistent with the EMH. This could also be an example of salience theory, where the investors focus on the attention-grabbing information and trade accordingly. For example, we see a positive significant reaction at the 5% level for the Communication Services sector the day after the event day of 0.47%.

The *CAAR*'s over the event window are primarily insignificant and the positive average abnormal returns are often reversed after the event day, which is in line with the findings of Born et al. (2017), who found that the effects of Trump's tweets are often very short-lived. This finding supports Hypothesis 7, that the effects are temporal rather than lasting. Nonetheless, the Materials sector and the Financial sector both show a negative significant *CAAR* over the event window for escalating tweets, which are not in line with Hypothesis 7. It must be stated that both of these were only significant for one test statistic.

The question remained whether the different reactions of sectors to Trump's tweets on the event day could be explained by whether a sector is cyclical or defensive. As explained in the previous paragraphs, some sectors reacted positively to escalating tweets, while others reacted negatively. The same pattern was observed for de-escalating tweets. The explanation for this is in line with the expectation. It was found that the difference in reaction to a Trump tweet could be very well explained by this classification.

To illustrate this for the escalating tweets, the cumulative average abnormal returns of sectors with high exposure belonging to each category are tracked over the event window, see Figure 4.1.

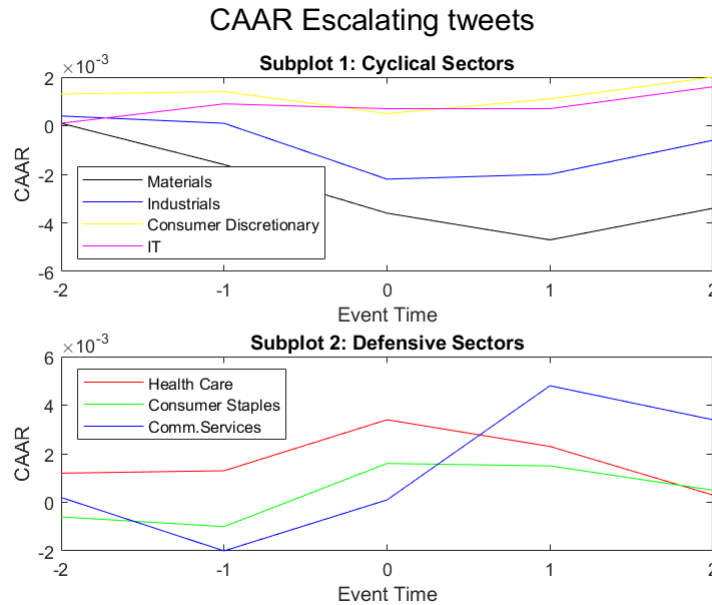


Figure 4.1: Escalating: Cyclical vs Defensive sectors

Figure 4.1, illustrates this interesting phenomenon. When Trump escalates the situation with China on Twitter, investors' perceived market risk seemingly rises and they consequently increase their demand for defensive stocks. This seems to explain the negative average abnormal return for cyclical sectors and the positive average abnormal return for defensive sectors during Trump's escalating tweets. It seems that these investors interpret Trump's tweets as a signal for upcoming tariffs and want to protect their investments by investing in more defensive sectors, indicating a "risk-off" sentiment in the market.

In recent years, the cyclical sectors have constantly outperformed defensive sectors in terms of returns and are therefore very interesting for investors (MSCI Research, 2019). This shift is visible when we track the cumulative average abnormal returns for Trump's de-escalating tweets, see Figure 4.2.

Figure 4.2, shows that when Trump de-escalates the situation with China on Twitter, the risk seems to be "on", and the investors shift their investments towards the more profitable cyclical sectors. Except for the Industrials sector, all cyclical sectors showed an increase in average abnormal return, while the defensive sectors showed the opposite. The sectors with significant findings support Hypotheses 3 & 4, which hypothesized that investors tend to shift their money away and towards cyclical sectors and vice versa for defensive sectors depending on the content

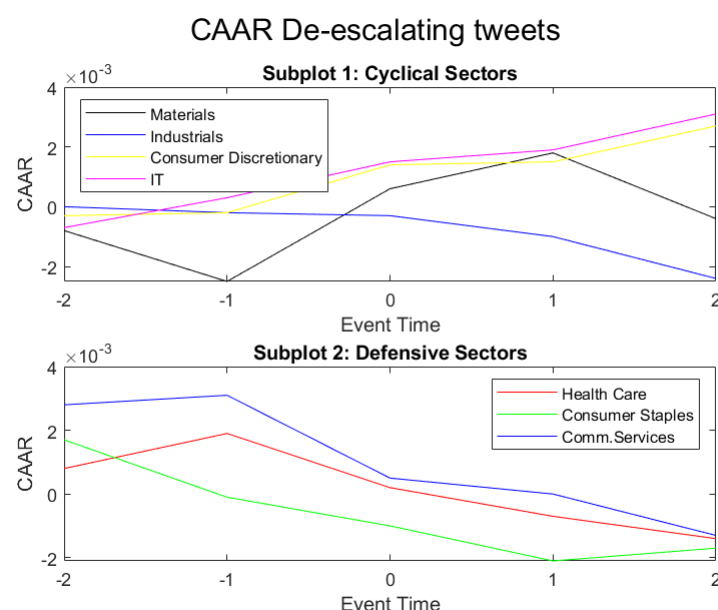


Figure 4.2: De-escalating: Cyclical vs Defensive sectors

of Trump's tweets. The de-escalating tweets from Trump seem to be interpreted as a reduced chance of future tariffs and a step closer towards a trade deal, reducing investors' perceived market risk.

The results observed on the event day might also be an example of salience theory, where investors overreact to signals given by Trump on Twitter. As the tweets are followed very carefully and the attention increases, investors might overreact to statements made by Trump that are often rather temporal than lasting. As discussed in Section 2.2.3, the tweets from Trump act as signals of the direction of the government and cause the investors to react to this information (Benton & Philips, 2020). Due to the relevance of the trade conflict and the unpredictable nature of Trump investors seem to over appreciate the relevance of some of the information shared by him on his Twitter account. Trump's tweets are often sentimental and his attitude can change in a week's notice. This could also be an explanation of why the price reaction is offset the days after the event day and the effect is not lasting. In general, the shift of the investors seemed to be more pronounced for escalating tweets. This is supported by Naveed, Gottron, Kunegis, & Alhadi (2011), who found that bad news tends to travel faster on Twitter than good news and receives more attention.

Another question remains why investors tend to shift their money primarily from and towards these specific sectors. Figure A.1, shows the results of the sector exposure analysis. The results indicated that the cyclical sectors: Materials, IT, Industrials, and Consumer Discretionary are all heavily exposed to tariffs from both countries. The explanation for this is very simple. Many

of the firms that are active in these sectors, manufacture and source their products in and from China. These sectors are very labour intensive and outsourcing to the attractive Chinese job market boosts their profit margins. Tariffs imposed by Trump on goods from China, would therefore also pressure the margins of these firms who need to import part of their products or raw materials back into the U.S. In addition, provocations from Trump may also lead to a reduction in sales in China. Firms in these sectors generally have a huge market in China and a boycott of U.S. products or tariffs imposed by China would hit them harder than any other sector.

Generally, the cyclical sectors are indeed more profitable during good economic times. Especially, the IT sector has been very profitable over the last decade. The defensive sectors are seen as a safe haven in times of financial distress and often protect the investor in times of economic downturn, but are mostly less profitable. This does not necessarily imply that the defensive sectors Health Care, Consumer Staples, and Communication Services are not exposed to tariffs. In fact, according to Figure A.1, these sectors are also exposed to the trade war. However, to fully understand why investors primarily seem to invest in these sectors as a "safe" alternative for the cyclical sectors we need to understand Trump's rhetoric.

During the U.S.- China trade conflict, the agricultural sector has always been his major show-piece. One of the main points of negotiation has been to improve the purchase of agricultural products by China. As illustrated by one of his tweets: "Our great Patriot Farmers will be one of the biggest beneficiaries of what is happening now. Hopefully, China will do us the honor of continuing to buy our great farm product the best but if not your Country will be making up the difference based on a very high China buy.....". Therefore, it is likely that investors may have shifted their money towards the Consumer Staples sector, of which the agricultural industry is part, when Trump escalated the situation towards China. Because this may have seemed like a sector that might eventually benefit from the tough negotiations. An explanation for the shift towards the Health Care sector is that Trump has suggested that the proceeds from the tariffs would be used to invest in the health care industry, therefore this sector might also be a good alternative when the argument escalates. For Communication Services and the other defensive sectors, this study observes a similar trend, to what we observe for Consumer Staples and Health Care. However, these sectors received less attention from Trump in his tweets and may therefore not be as attention-grabbing. In general, the significant results found for these sectors can be explained logically and are in line with the expectations.

Table 4.2: Abnormal Returns Content-Based categorisation

Content-Based categorisation							
Sector	Category	AAR					CAAR
		-2	-1	0	1	2	[-2,2]
Materials	0	-0.0008	-0.0017	0.0031**+	0.0012	-0.0022	0.0011
	1	0.0001	-0.0017**+	-0.0020	-0.0011	0.0013	-0.0033 ⁺
IT	0	-0.0007	0.0010	0.0012	0.0004	0.0012	0.0034
	1	0.0001	0.0008	-0.0002	0.0000	0.0009	0.0016
Health Care	0	0.0008	0.0011	-0.0017	-0.0009	-0.0007	-0.0013
	1	0.0012	0.0001	0.0021**+	-0.0011	-0.0020*	0.0003
Consumer Staples	0	0.0017*	-0.0018	-0.0009	-0.0011	0.0004	-0.0018
	1	-0.0006	-0.0004	0.0026***+	-0.0001	-0.0010	0.0004
Industrials	0	0.0000	-0.0002	-0.0001	-0.0007	-0.0014 ⁺	-0.0022
	1	0.0004	-0.0003	-0.0023***+	0.0002	0.0014**+	-0.0005
Consumer Discretionary	0	-0.0003	0.0001	0.0016***+	0.0001	0.0012	0.0027
	1	0.0013	0.0001	-0.0009	0.0006 ⁺	0.0009	0.0019
Communication Services	0	0.0028	0.0003	-0.0026	-0.0005	-0.0013	-0.0014
	1	0.0002	-0.0022	0.0021	0.0047***+	-0.0014	0.0035
Energy	0	-0.0006	-0.0008	-0.0006	0.0015	0.0005	-0.0002
	1	0.0007	0.0000	-0.0018	0.0014	0.0016	0.0019
Financials	0	-0.0014	-0.0023* ⁺	-0.0011	0.0019	-0.0024 ⁺	-0.0056
	1	-0.0034***+	-0.0009	-0.0008	-0.0021*	-0.0007	-0.0080**
Utilities	0	0.0009	0.0009	-0.0011	-0.0009	0.0030***+	0.0026
	1	-0.0004	-0.0015	0.0021	0.0027	-0.0038	-0.0010
Real Estate	0	0.0002	0.0010	-0.0009	-0.0013	0.0038***+	0.0003
	1	0.0000	0.0000	0.0013	-0.0014	0.0005	0.0004

0 = de-escalating and 1 = escalating

t-test stat. sig. ** at 5% level * at 10% level : degrees of freedom = groupsincat-2

rank-test stat. sig. ** at 5% level + at 10% level

Note: This table shows the AAR and CAAR of the event window for the content-based classification. Significance is evaluated using two-sided tests. Sectors are ranked from high to low exposure and defensive sectors are in bold font.

4.3 Sentiment-Based categorisation

In this section, the results from the sentiment by polarity classification are highlighted. Table 4.3, shows the average abnormal returns of the sector portfolio during the event window aggregated over the categories, as specified in Section 3.3.1. Alike the previous section, the main inference is from the reaction on the event day itself. The results from the categorisation based on sentiment showed similar results as the results of the content-based classification. On the event day, this study observed a significant positive reaction to de-escalating tweets for the Materials sector. Economically, the market for the Materials sector went up with on average 0.25%. For escalating tweets on the event day, this study observed a significant positive reaction at the 5% level for the Consumer Staples sector and at the 10% level (rank test) for the Consumer Discretionary sector. Respectively, 0.35% and 0.18% daily positive abnormal returns. In contrast, significant negative reactions at the 10% level were found for Materials (rank test) and the Industrials sector. Where the former had a reaction of -0.41% and the latter reacted with -0.23%. These findings again support Hypothesis 1, that Trump's tweets can indeed lead to abnormal returns for sectors. For the other sectors, no significant reactions were found on the event day, which is in line with the sector exposure. Sectors with low exposure to the trade war were not expected to show a significant reaction to Trump's tweets. However, different reactions from the sectors were observed. For example, a positive (IT) and negative (Health Care) insignificant reaction to de-escalating tweets and a positive (Health Care) reaction to escalating tweets.

For days around the event day, this study observes similar significant results as for the content-based categorisation. On the days before negative tweets of Trump, this study observes, next to significant reactions on the event day itself, some anticipation a few days before the event. Primarily, for the Materials and Industrials sectors. A reason for this could be that investors sense negative sentiment in the market and within Trump's administration about the current progress of the trade deals and already divert their investments. For the Materials sector, this study observed a negative significant reaction the day before a positive tweet by Trump. An explanation could be that investors anticipated bad news based on surrounding factors and were subsequently surprised by the positive sentiment of Trump's tweets on the event day. This could explain the switch in the sign for the Materials sector between the day before and on the event day itself. For the days after the event day, this study observed a similar pattern to the results obtained from the content-based classification.

Some significant cumulative abnormal returns were found. The Industrials, Consumer Discretionary, and Financials sectors showed statistically significant results for both significance

tests. Respectively, the Industrials, and Financials sector had a negative reaction of -0.52% and 1.25%, and the Consumer Discretionary sector had a positive reaction of 0.62% over the event window, which is not in line with Hypothesis 7. However, these significant cumulative abnormal returns should be interpreted with care, especially when a sector had not shown a significant reaction on the event day itself, such as Financials. The reason for this is that by coincidence, due to the small sample size of negative tweets, results can be predominantly negative. When these negative results accumulate, such as for Financials, the cumulative abnormal returns might turn out statistically significant where in fact they are not. In comparison, no significant cumulative abnormal returns were found for the positive sentiment tweets, which had a larger sample. In general, it is found that significant results of the event day are offset and reversed by returns on subsequent days, which does support Hypothesis 7 implying that the effects are temporal rather than lasting.

To explain the different reactions of sectors to tweets containing positive and negative sentiment, the sectors were again divided into cyclical sectors and defensive sectors. Starting with the sector reactions to negative sentiment tweets, see Figure 4.3.

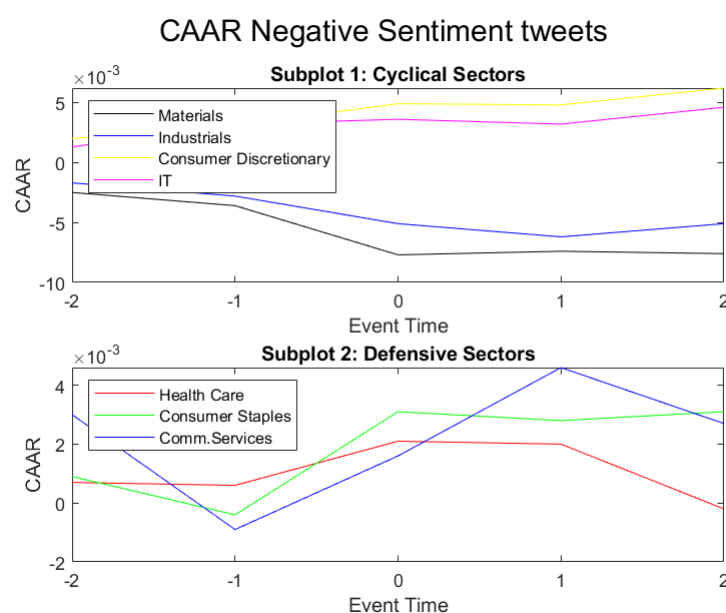


Figure 4.3: Negative Sentiment: Cyclical vs Defensive sectors

In Figure 4.3, this division showed that negative sentiment tweets caused a negative reaction on the event day for the cyclical sectors, with the exception of Consumer Discretionary. Contrary to the cyclical sectors, the defensive sectors Health Care, Consumer Staples, and Communication Services showed a sharp positive reaction to the negative sentiment tweets. Therefore, these results also suggest that investors shift their money away from cyclical sectors towards defensive

sectors when Trump tweets contain negative sentiment. For tweets that contain positive sentiment, see Figure 4.4.

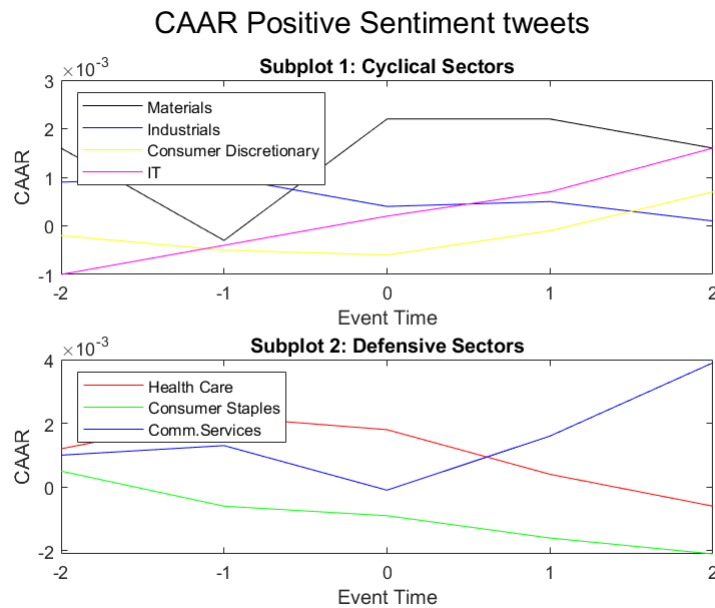


Figure 4.4: Positive Sentiment: Cyclical vs Defensive sectors

For these tweets, the market reactions seem to have reversed. Except for the Industrials and to a lesser extent the Consumer Discretionary sector, this study observed an upward reaction for the cyclical sectors on the event day. Opposed to the upward reaction of the cyclical sectors, the defensive sectors displayed a downward trend. Therefore, these results suggest that investors shift their money away from the defensive sectors and back towards the cyclical sectors when Trump tweets contain positive sentiment.

In sum, the sentiment-based categorisation also supported indications that investors tend to shift their money between cyclical and defensive sectors depending on Trump's tweets characteristics, where the significant results support Hypotheses 5 & 6. Although, it must be stated that the reactions as hypothesized are more supported by negative sentiment tweets than by positive sentiment tweets. Indicating that investors tend to respond more to negative news, which was also found for the escalating tweets and is in line with Naveed et al. (2011).

Table 4.3: Abnormal Returns Sentiment by Polarity categorisation

Sentiment Analysis categorisation							
Sector	Category	AAR					CAAR
		-2	-1	0	1	2	[-2,2]
Materials	0	0.0016	-0.0019***+	0.0025***+	0.0000	-0.0006	0.0015
	1	-0.0025 ⁺	-0.0011	-0.0041 ⁺	0.0003	-0.0002	-0.0076 ⁺
IT	0	-0.0010**+	0.0006	0.0006	0.0005	0.0009	0.0017
	1	0.0013	0.0019	0.0004	-0.0004	0.0014	0.0045
Health Care	0	0.0012	0.0010	-0.0004	-0.0014	-0.0010	-0.0007
	1	0.0007	-0.0001	0.0015	-0.0001	-0.0022	-0.0002
Consumer Staples	0	0.0005	-0.0011	-0.0003	-0.0007	-0.0005	-0.0022
	1	0.0009	-0.0013	0.0035***+	-0.0003	0.0003	0.0032
Industrials	0	0.0009	0.0001	-0.0006	0.0001	-0.0004	0.0001
	1	-0.0017**+	-0.0011	-0.0023**+	-0.0011	0.0011	-0.0052***+
Consumer Discretionary	0	-0.0002	-0.0003	-0.0001	0.0005	0.0008	0.0008
	1	0.0020 ⁺	0.0011	0.0018 ⁺	-0.0001	0.0014	0.0062***+
Communication Services	0	0.0010	0.0003	-0.0014	0.0017	-0.0011	0.0003
	1	0.0030	-0.0039	0.0025	0.0030**	-0.0019	0.0027
Energy	0	-0.0001	-0.0007	-0.0007	0.0017	0.0023	0.0025
	1	0.0003	0.0002	-0.0023	0.0008	-0.0020	-0.0030
Financials	0	-0.0016*	-0.0014	-0.0004	0.0005	-0.0015	-0.0045*
	1	-0.0042**+	-0.0024	-0.0027	-0.0014	-0.0018	-0.0125***+
Utilities	0	0.0011	0.0007	0.0011	-0.0011	0.0004	0.0021
	1	-0.0019	-0.0026	-0.0013	0.0058**+	-0.0023	-0.0023
Real Estate	0	0.0004	-0.0007	0.0003	-0.0021	0.0032***+	0.0007
	1	-0.0006	0.0001	-0.0001	0.0004	-0.0003	-0.0006

0 = negative and 1 = positive sentiment

t-test stat. sig. ** at 5% level * at 10% level: degrees of freedom = groupsincat-2

rank-test stat. sig. ** at 5% level + at 10% level

Note: This table shows the AAR and CAAR of the event window for the sentiment-based classification. Significance is evaluated using two-sided tests. Sectors are ranked from high to low exposure and defensive sectors are in bold font.

4.4 Content-Based vs. Sentiment-Based categorisation

In this section, the relationships and results between the content-based and sentiment-based categorisation are discussed. In essence, this study discusses the differences and similarities between the manual classification and the classification by a software package. Generally, the average abnormal returns of both classification methods were strongly correlated ($\rho = 0.69$), see Figure 4.5. This indicates that, on average, the software package can adequately capture the content of the message. Although the software packages are rapidly improving, they are unable to detect any form of irony or sarcasm in messages. Irony and sarcasm are not uncommon in Trump's tweets and would bias the polarity. In turn, the software package is not biased by any form of subjectivity or a lack of consistency. Even though evaluated with great care, manual classification is subjective and can be inconsistent, which might bias the results. The differences between the two categorisation methods can be best explained in the form of an example: "Our economy is the best in the world by far. Lowest unemployment ever within almost all categories. Poised for big growth after trade deals are completed. Import prices down China eating Tariffs. Helping targeted Farmers from big Tariff money coming in. Great future for USA!". This tweet was classified by Sentimentr as a message with positive sentiment, logical because the message has been brilliantly window-dressed by Trump. However, this message is part of multiple tweets emphasizing the degree in which China is "suffering" from the tariffs imposed by the Trump administration. In no way, this tweet suggests good progress being made in the relationship between the two countries, certainly not when he states that China "is eating" the tariffs imposed by himself and "Great future for the USA". Therefore, this study would classify this tweet as provocative and thus escalating the argument between the two countries.

Despite, these differences in interpretation between manual content-based classification and software-based classification, both results drew similar conclusions. Both methods found indications for investors shifting their investments between cyclical and defensive sectors depending on the nature of Trump's tweets. The results obtained from the content-based classification more accurately captured this relationship compared to the sentiment-based classification, which is likely due to the example shown earlier.

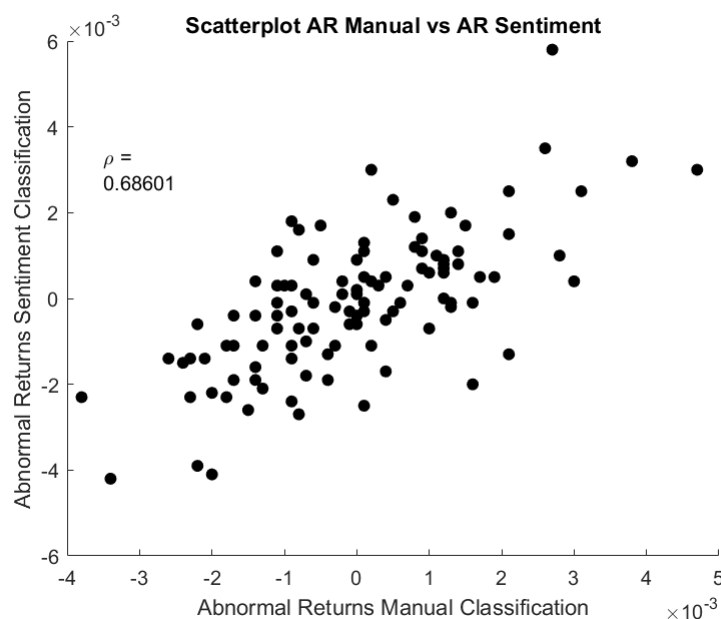


Figure 4.5: AR manual versus AR software

4.5 Robustness Checks

To check the robustness, this study conducted two main tests. Firstly, the length of the estimation window was set to 180 days to test whether the results of the study were sensitive to changes in the estimation window length. Secondly, this study tested robustness by replicating the methodology for a sample of pre-presidency Trump tweets on China, see Table A.4. According to the reasoning in Section 3.2.1, these sample of tweets should provide mainly insignificant results.

The results shown in Tables A.2 & A.3 of the appendix, suggested that the results were robust to changes in the estimation window length. Changing the estimation window did not lead to a change in the interpretation of the hypotheses. This result is in line with the findings of Kothari & Warner (1985), who suggested that the length of the estimation window does not significantly impact the results of a short-term event study.

The sample of tweets before his election did not contain any de-escalating tweets, therefore only escalating tweets are considered. During this time, Trump seemed to be very frustrated with China. The results of the content-based categorisation do not show any significant results for sectors with high exposure, nor do they show an indication of a pattern, see Tables A.5 & A.6 in the appendix. Differences between sectors could no longer be explained by the categorisation in cyclical and defensive sectors. The results do find some occasional significance around the event day, which could be explained by noise or randomness. This could be a reason because these deviations were inconsistent between sectors and within the sectors themselves.

The sectors that showed significant results in the presidential sample, do not show any sign of significance in the sentiment analysis of the pre-presidential sample. In general, the results of the pre-presidential sample cannot reject that there is no significant relationship between Trump's tweets and sector stock returns.

Therefore, the results of the robustness checks are in line with the expectations and improve the robustness of the results obtained in the study, no indications were found that lead to a different interpretation of the hypotheses.

Conclusion & Discussion

5.1 Conclusion

This study aimed to identify the effect of Trump's U.S.-China trade conflict-related tweets on the stock returns of U.S. sectors. Based on the quantitative results this study finds a significant relationship between Trump's tweets and the abnormal returns of some U.S. sectors.

The results indicate that several sectors with higher exposure to the trade war react significantly to Trump's tweets. Overall, this study observes a pattern that indicates investors shifting their money from cyclical sector stocks towards defensive sector stocks when Trump escalates the situation or when his tweets contain negative sentiment. This study also finds indications that investors shift their investments back to cyclical sectors stocks when Trump de-escalates the situation or his tweets contain positive sentiment. Generally, the effects of Trump's tweets seem to be temporal rather than lasting. In addition, this study also shows that both the manual classification and the software-based sentiment classification can observe the aforementioned pattern, however, this pattern is more clearly observed for the content-based classification.

In sum, the results of this study indicate that U.S. sectors are significantly affected by Trump's tweets and react differently based on tweet characteristics.

5.2 Discussion

5.2.1 Implications of findings

The results from this study generally agree with the hypotheses. Especially, this study is, to my best knowledge, the only academic study that confirms that Trump's tweets on the U.S.-China trade war affect the stock returns of U.S. sectors. Therefore, this study addresses a "gap" in literature. The results from this study are in line with studies that suggest that investors tend to seek a "safe" haven in times of uncertainty and interpret the sentiment of a tweet. It

seems that investors see Trump's tweets as a signal and trade primarily on the direction that they expect his policy to go. Since Trump's tweets are often very attention-grabbing, salience theory suggests that this may cause investors to overreact on Trump's tweets. Somewhat unexpected, this study finds some significance before the event day. This is unexpected since information leakage was deemed unlikely in the case of Trump's tweets.

This study builds on the findings of other studies and shows indications that Trump's tweets are indeed important to financial markets. Especially, this study adds that Trump's presidential tweets seem to have a significant impact on the returns of entire sectors instead of individual firms. This confirms that investors and market analysts should continue to monitor Trump's Twitter account and anticipate the consequences that his posts might have. This advice is mostly for day traders or companies who profit from market fluctuations such as High-Frequency Traders. Long-term investors should not be bothered by most of his tweets.

5.2.2 Limitations

A limitation of this study is that there exists limited reference for this study in academic research. The topic is relatively new and there is no general approach. Typically, the caution with this type of study is that it remains very hard to distinguish whether the reactions are caused solely by Trump's tweets or by missing to identify other confounding factors. Although the appreciation for Trump's tweets has grown, using daily data may cause other events to offset or amplify the effects of the tweets. An example of this might be the significance observed around the event day itself. Although the main focus of the study was on the event day itself, some effects before the event day were hard to explain. Especially, due to the construction of this method no tweets were included before the event day itself, and initially no information leakage was expected. Another limitation that arises from a solution was that for some groups tweets were included on the days after the event day. In general, these results were insignificant, but they make it hard to observe whether the effects are lasting.

Furthermore, the nature of Twitter with fast succeeding tweets, was solved by grouping the tweets to be able to improve the methodology. However, the decision to group the tweets also has a side effect. The grouping of tweets resulted in a limited amount of observations, causing a higher probability of randomness in the results, resulting in a Type-I error. Although, the results of this study do find strong suggestions of a robust pattern and directional significance is conservatively evaluated (two-sided test), the results should still be interpreted with care. Additionally, the limitations of this study are in the pitfalls of using manual content-based classification and software-based classification. On the one hand, manual classification is

prone to subjectivity, which can cause bias. On the other hand, software-based classification is unable to detect some underlying irony or sarcasm, which could lead to bias as well.

The exposure of the sectors fails to take into account the benefits of reduced domestic competition from Chinese manufacturers that export to the U.S.

Despite these limitations, this study and its methodology can be justified as they provide some new relevant insights to the relationship between Trump's tweets and financial markets. More specifically, how U.S. sectors react to the live coverage of an economically relevant event on social media by the president of the U.S.

5.2.3 Suggestions for further research

The U.S.-China trade conflict is still not over. This study has included tweets sent by Trump until the completion of the Phase One deal.

In the future, when a final deal is settled, studies can expand the data set and thereby improve the robustness of this study. In addition, further studies can be conducted to find more insights into the causality of Trump's tweets and market reactions. Furthermore, studies can focus on identifying differences between industries within a sector. While this study focused on sectors, there may exist notable differences in the reaction between industries. Further research may also focus on whether the same results are observed for Trump tweets in other trade conflicts, such as with the trade conflict with Europe or NAFTA. Moreover, studies could focus on the effects of Trump's tweets on Chinese listed companies. It would also be interesting to use hourly data since this would improve the robustness of the results. Another possible research topic is whether other politicians are able to affect financial markets via their social media accounts.

Finally, Trump's tweets make the headlines of today and will most likely make the headlines of tomorrow.

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Appendices

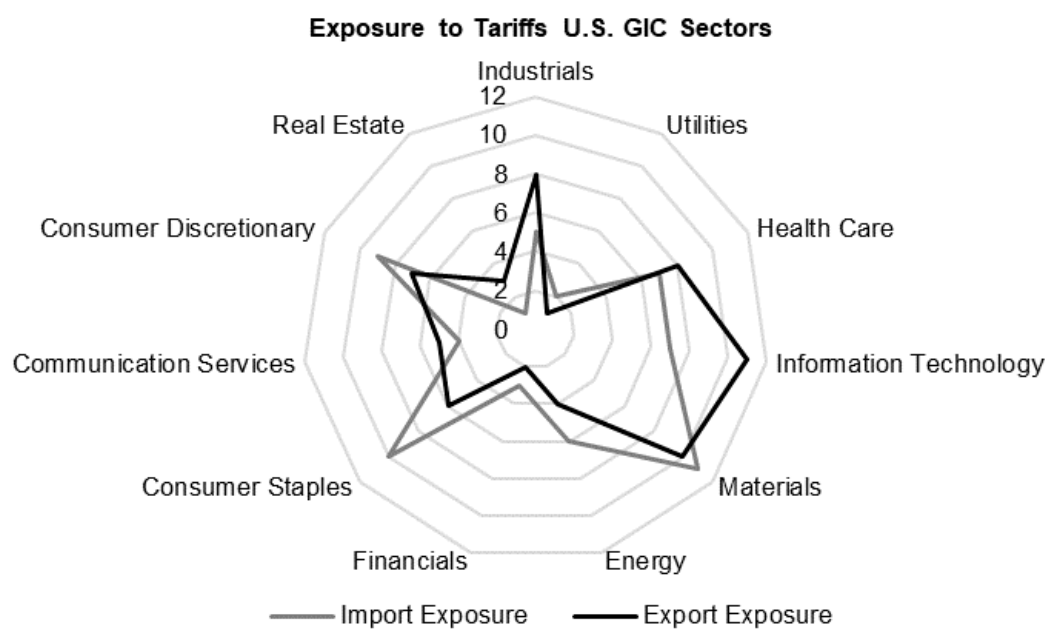


Figure A.1: Exposure GICS sectors to U.S.-China trade war

Note: This figure shows the crude import and export exposure of the GICS sectors based on the methodology explained in section 3.3.6. A higher score implies a higher exposure to the trade conflict.

Table A.1: Event days, Sample tweets and categorisation

Event day	Sample Tweet	Content-Based	average Sentiment
12-31-2019	I will be signing our very large and comprehensive Phase One Trade Deal with China on January 15. The ceremony will take place at the White House. High level representatives of China will be present. At a later date I will be going to Beijing where talks will begin on Phase Two!	0	0.278
12-20-2019	Had a very good talk with President Xi of China concerning our giant Trade Deal. China has already started large scale purchases of agricultural product & more. Formal signing being arranged. Also talked about North Korea where we are working with China & Hong Kong (progress!).	0	0.281
12-12-2019	Getting VERY close to a BIG DEAL with China. They want it and so do we!	0	0.202
11-18-2019	Our great Farmers will receive another major round of "cash" compliments of China Tariffs prior to Thanksgiving. The smaller farms and farmers will be big beneficiaries. In the meantime and as you may have noticed China is starting to buy big again. Japan deal DONE. Enjoy!	0	0.322
10-31-2019	China and the USA are working on selecting a new site for signing of Phase One of Trade Agreement about 60% of total deal after APEC in Chile was canceled due to unrelated circumstances. The new location will be announced soon. President Xi and President Trump will do signing!	1	0.193
10-10-2019	Good things are happening at China Trade Talk Meeting. Warmer feelings than in recent past more like the Old Days. I will be meeting with the Vice Premier today. All would like to see something significant happen!	0	0.334
9-12-2019	It is expected that China will be buying large amounts of our agricultural products!	0	0.000
8-30-2019	wanting to give up on our very successful Trade battle with China which has had its worst Economic year in memory (and getting worse). We are taking in \$Billions. Will be big for Farmers and ALL!	1	-0.189
8-23-2019	For many years China (and many other countries) has been taking advantage of the United States on Trade Intellectual Property Theft and much more. Our Country has been losing HUNDREDS OF BILLIONS OF DOLLARS a year to China with no end in sight....	1	0.153
8-12-2019	China wants to make a deal so badly. Thousands of companies are leaving because of the Tariffs they must stem the flow. At the same time China may be hoping for a Democrat to win so they could continue the great ripoff of America & the theft of hundreds of Billions of \$'s!	1	0.222
8-1-2019	...during the talks the U.S. will start on September 1st putting a small additional Tariff of 10% on the remaining 300 Billion Dollars of goods and products coming from China into our Country. This does not include the 250 Billion Dollars already Tariffed at 25%...	1	0.085
7-11-2019	Mexico is doing great at the Border but China is letting us down in that they have not been buying the agricultural products from our great Farmers that they said they would. Hopefully they will start soon!	1	0.126
7-1-2019	I had a great meeting with President Xi of China yesterday far better than expected. I agreed not to increase the already existing Tariffs that we charge China while we continue to negotiate. China has agreed that during the negotiation they will begin purchasing large.....	0	0.426
6-11-2019	If Mexico produces (which I think they will). Biggest part of deal with Mexico has not yet been revealed! China is similar except they devalue currency and subsidize companies to lessen effect of 25% Tariff. So far little effect to consumer. Companies will relocate to U.S.	1	-0.193
5-10-2019	Tariffs will make our Country MUCH STRONGER not weaker. Just sit back and watch! In the meantime China should not renegotiate deals with the U.S. at the last minute. This is not the Obama Administration or the Administration of Sleepy Joe who let China get away with "murder!"	1	0.184
5-6-2019	of additional goods sent to us by China remain untaxed but will be shortly at a rate of 25%. The Tariffs paid to the USA have had little impact on product cost mostly borne by China. The Trade Deal with China continues but too slowly as they attempt to renegotiate. No!	1	-0.016
3-4-2019	I have asked China to immediately remove all Tariffs on our agricultural products (including beef pork etc.) based on the fact that we are moving along nicely with Trade discussions....	0	0.246
2-25-2019	China Trade Deal (and more) in advanced stages. Relationship between our two Countries is very strong. I have therefore agreed to delay U.S. tariff hikes. Let's see what happens?	0	0.223
1-31-2019	Looking for China to open their Markets not only to Financial Services which they are now doing but also to our Manufacturing Farmers and other U.S. businesses and industries. Without this a deal would be unacceptable!	1	-0.295
1-22-2019	China posts slowest economic numbers since 1990 due to U.S. trade tensions and new policies. Makes so much sense for China to finally do a Real Deal and stop playing around!	1	0.095
12-31-2018	Just had a long and very good call with President Xi of China. Deal is moving along very well. If made it will be very comprehensive covering all subjects areas and points of dispute. Big progress being made!	0	0.430
12-14-2018	China just announce the there economy is growing much slower than anticipated because of our Trade War with them. They have just suspended U.S. Tariff Hikes. U.S. is doing very well. China wants to make a big and very comprehensive deal. It could happen and rather soon!	0	0.170
12-3-2018	President Xi and I have a very strong and personal relationship. He and I are the only two people that can bring about massive and very positive change on trade and far beyond between our two great Nations. A solution for North Korea is a great thing for China and ALL!	0	0.255
11-1-2018	Just had a long and very good conversation with President Xi Jinping of China. We talked about many subjects with a heavy emphasis on Trade. Those discussions are moving along nicely with meetings being scheduled at the G-20 in Argentina. Also had good discussion on North Korea!	0	0.275
9-26-2018	China is actually placing propaganda ads in the Des Moines Register and other papers made to look like news. That's because we are beating them on Trade opening markets and the farmers will make a fortune when this is over! https://t.co/ppdvTX7oz1	1	-0.013
9-17-2018	Tariffs have put the U.S. in a very strong bargaining position with Billions of Dollars and Jobs flowing into our Country - and yet cost increases have thus far been almost unnoticeable. If countries will not make fair deals with us they will be "Tariffed!"	1	0.042
9-10-2018	If the U.S. sells a car into China there is a tax of 25%. If China sells a car into the U.S. there is a tax of 2%. Does anybody think that is FAIR? The days of the U.S. being ripped-off by other nations is OVER!	1	0.173
8-6-2018	Tariffs are working far better than anyone ever anticipated. China market has dropped 27% in last 4months and they are talking to us. Our market is stronger than ever and will go up dramatically when these horrible Trade Deals are successfully renegotiated. America First.....	1	-0.008
6-4-2018	China already charges a tax of 16% on soybeans. Canada has all sorts of trade barriers on our Agricultural products. Not acceptable!	1	-0.159
5-21-2018	Under our potential deal with China they will purchase from our Great American Farmers practically as much as our Farmers can produce.	0	0.227
5-14-2018	China and the United States are working well together on trade but past negotiations have been so one sided in favor of China for so many years that it is hard for them to make a deal that benefits both countries. But be cool it will all work out!	0	0.014
5-1-2018	Delegation heading to China to begin talks on the Massive Trade Deficit that has been created with our Country. Very much like North Korea this should have been fixed years ago not now. Same with other countries and NAFTA...but it will all get done. Great Potential for USA!	0	0.107
4-9-2018	We are not in a trade war with China that war was lost many years ago by the foolish or incompetent people who represented the U.S. Now we have a Trade Deficit of \$500 Billion a year with Intellectual Property Theft of another \$300 Billion. We cannot let this continue!	1	0.305
3-2-2018	China has been asked to develop a plan for the year of a One Billion Dollar reduction in their massive Trade Deficit with the United States. Our relationship with China has been a very good one and we look forward to seeing what ideas they come back with. We must act soon!	1	-0.073
11-10-2017	I don't blame China I blame the incompetence of past Admins for allowing China to take advantage of the U.S. on trade leading up to a point where the U.S. is losing \$100's of billions. How can you blame China for taking advantage of people that had no clue? I would've done same!	0	-0.178
10-25-2017	Spoke to President Xi of China to congratulate him on his extraordinary elevation. Also discussed NoKo & trade two very important subjects!	0	0.168
7-31-2017	I am very disappointed in China. Our foolish past leaders have allowed them to make hundreds of billions of dollars a year in trade yet...	1	-0.453
7-10-2017	Leaving Hamburg for Washington D.C. and the WH. Just left China's President Xi where we had an excellent meeting on trade & North Korea.	0	0.132
4-11-2017	I explained to the President of China that a trade deal with the U.S. will be far better for them if they solve the North Korean problem!	0	0.208
3-31-2017	The meeting next week with China will be a very difficult one in that we can no longer have massive trade deficits...	0	-0.192

Note: This table shows the event days, a sample tweet, the content-based classification and the average sentiment of every group.

Table A.2: Abnormal Returns Content-Based Classification: Robustness Check

Content-Based categorisation 180 day estimation window							
Sector	Category	AAR					CAAR
		-2	-1	0	1	2	[-2,2]
Materials	0	0.0010	-0.0014	0.0034***+	0.0013	-0.0021	0.0021
	1	-0.0004	-0.0014	-0.0019	0.0008	-0.0015	-0.0023
IT	0	-0.0011 ⁺	0.0008	0.0010	-0.0010	0.0008	0.0017
	1	-0.0003	0.0005	-0.0007	-0.0003	0.0005	-0.0003
Health Care	0	0.0011	0.0013	-0.0015	-0.0006	-0.0004	0.0000
	1	0.0014	0.0004	0.0024***+	-0.0009	-0.0018	0.0016
Consumer Staples	0	0.0019***+	-0.0018	-0.0010	-0.0006	0.0007	-0.0010
	1	-0.0006	-0.0003	0.0030***++	-0.0000	-0.0007	0.0014
Industrials	0	0.0001	-0.0002	-0.0001	-0.0007	-0.0014	-0.0021
	1	0.0004	-0.0002	-0.0023*+	0.0002	0.0014 ⁺	-0.0004
Consumer Discretionary	0	-0.0004	0.0002	0.0016***+	-0.0001	0.0011	0.0027
	1	0.0013 ⁺	0.0001	-0.0010 ⁺	0.0006 ⁺	0.0008	0.0019
Communication Services	0	0.0032	0.0001	-0.0026	0.0006	-0.0008	0.0003
	1	0.0002	-0.0019	0.0030*	0.0048**	-0.0007	0.0054
Energy	0	-0.0001	-0.0003	-0.0001	0.0021	0.0011	0.0025
	1	0.0012	0.0005	-0.0012	0.0019	0.0022	0.0047
Financials	0	-0.0018**	-0.0021	-0.0012	0.0008	-0.0029*+	-0.0073***+
	1	-0.0034***+	-0.0012	-0.0017	-0.0022	-0.0014	-0.0099***+
Utilities	0	0.0011	0.0006	-0.0013	0.0002	0.0035*+	0.0036
	1	-0.0006	-0.0014	0.0029	0.0026	-0.0033	0.0002
Real Estate	0	0.0005	-0.0008	-0.0007	-0.0008	0.0041***+	0.0016
	1	0.0002	0.0003	0.0017	-0.0013	0.0009	0.0018

0 = negative and 1 = positive sentiment

t-test stat. sig. ** at 5% level * at 10% level: degrees of freedom = groupsincat-2

rank-test stat. sig. ++ at 5% level + at 10% level

Note: This table shows the AAR and CAAR of the event window for the content-based classification. Significance is evaluated using two-sided tests. Sectors are ranked from high to low exposure and defensive sectors are in bold font. This table used an estimation window length of 180-days.

Table A.3: Abnormal Returns Sentiment by Polarity Classification: Robustness Check

Sentiment Analysis categorisation 180 day Estimation Window							
Sector	Category	AAR					CAAR
		-2	-1	0	1	2	[-2,2]
Materials	0	0.0019	-0.0017***	0.0027***	0.0002	-0.0005	0.0025
	1	-0.0023	-0.0008	-0.0038	0.0004	0.0008	-0.0064
IT	0	-0.0013***	0.0003	0.0002	0.0000	0.0005	-0.0001
	1	0.0009	0.0017	0.0001	-0.0008	0.0011	0.0030
Health Care	0	0.0014*	0.0012	-0.0002	-0.0011	-0.0007	-0.0007
	1	0.0010	0.0001	0.0017	0.0002	-0.0020	0.0010
Consumer Staples	0	0.0006	-0.0010	-0.0001	-0.0004	-0.0001	-0.0012
	1	0.0012	-0.0014	0.0036***	-0.0001	0.0003	0.0036
Industrials	0	0.0009	0.0001	-0.0006	0.0001	-0.0004	0.0002
	1	-0.0017 ⁺	-0.0011	-0.0023* ⁺	-0.0011	0.0011	-0.0052 ⁺
Consumer Discretionary	0	-0.0002	-0.0003	-0.0001	0.0005	0.0008	0.0008
	1	0.0020 ⁺	0.0011	0.0018 ⁺	-0.0001	0.0014	0.0062***
Communication Services	0	0.0011	0.0004	-0.0009	0.0023	-0.0003	0.0025
	1	0.0034	-0.0042	0.0027	0.0036***	-0.0020	0.0035
Energy	0	0.0004	-0.0002	-0.0002	0.0023 ⁺	0.0029	0.0051
	1	0.0009	0.0007	-0.0017	0.0014	-0.0015	-0.0003
Financials	0	-0.0018**	-0.0015	-0.0008	-0.0001	-0.0024 ⁺	-0.0067**
	1	-0.0046***	-0.0021	-0.0029	-0.0019	-0.0017	-0.0132***
Utilities	0	0.0010	0.0007	0.0014	-0.0005	0.0013	0.0037
	1	-0.0015	-0.0032	-0.0013	0.0062***	-0.0027	-0.0024
Real Estate	0	0.0006	-0.0005	0.0006	-0.0017 ⁺	0.0036***	0.0021
	1	-0.0003	0.0002	0.0001	0.0007	-0.0002	0.0005

0 = negative and 1 = positive sentiment

t-test stat. sig. ** at 5% level * at 10% level: degrees of freedom = groupsincat-2

rank-test stat. sig. *** at 5% level + at 10% level

Note: This table shows the AAR and CAAR of the event window for the sentiment-based classification. Significance is evaluated using two-sided tests. Sectors are ranked from high to low exposure and defensive sectors are in bold font. This table used an estimation window length of 180-days.

Table A.4: Robustness Check Pre-Presidency tweet sample

Event Day	Sample Tweet	Content-Based	avg. Sentiment
4-23-2015	China has a backdoor into the Trans-Pacific Partnership. This deal does not address currency manipulation. China is laughing at us.	1	0.273
12-10-2014	China is ripping wealth out Africa and yet as usual refuses to put anything back to help with Ebola. "Let the stupid Americans do it!" SAD	1	-0.113
11-25-2014	As China and the rest of the World continue to rip off the U.S. economically they laugh at us and our president over the riots in Ferguson!	1	-0.149
11-18-2014	Obama's China 'climate' deal binds America with language of 'will' curb emissions now while China only 'intends' to curb in 2030. Bad deal!	1	-0.061
10-30-2014	Chinese oil trader just bought "record number" of Mideast crude http://t.co/ocwvpfElji China gains while we fight ISIS. What are we doing?	1	-0.295
6-4-2014	US trade deficit hit \$64B+ in April 2 yr record high http://t.co/e5RuDJxexp We must do better. China is ripping us. Bring the jobs home!	1	-0.062
5-20-2014	A classic - China just signs massive oil and gas deal with Russia giving Russia plenty of ammo to continue laughing in U.S. face.	1	0.449
7-29-2013	The new reality – China's demand for oil now controls the market http://t.co/lqKTTsyCoQ And OPEC gets away with ripping us off at \$105!	1	0.060
4-17-2013	The Chinese must still be laughing at Kerry's trip to China. He got nothing gave them everything and promised even more.	1	0.229
2-26-2013	China is buying gas fields in Texas http://t.co/G6tW5gSKti & stealing our corporate secrets...	1	-0.177
2-5-2013	China is buying our shale and gas fields http://t.co/T4bu11CK & Obama still won't approve Keystone http://t.co/Rr94yvAV Pathetic!	1	0.164
1-31-2013	Obama's speech in Las Vegas yesterday cost the taxpayer 520perwordandover1.6M http://t.co/W7OVfZvz More money borrowed from China.	1	0.271
1-23-2013	In 2010 alone our trade deficit with China cost over 566000 jobs http://t.co/u9gb8nY9 This is unsustainable for the American worker.	1	-0.334
1-8-2013	Trade with China has killed over 29% of US manufacturing jobs in the US http://t.co/qae9jppzZ China is robbing us blind!	1	-0.261
12-20-2012	China is robbing us blind in trade deficits and stealing our jobs yet our leaders are claiming 'progress' http://t.co/2r9DHxHo SAD!	1	-0.408
12-10-2012	China is buying so many of our companies– it's really getting bad.	1	0.102
11-21-2012	Direct foreign investments continue to flow into China at over \$100B a year http://t.co/jtmBTMgw That's money that could be spent here.	1	0.061
10-11-2012	Even with lower profit projections American firms are still throwing money into China http://t.co/xRJlsqB Obama is killing investment.	1	-0.033
10-5-2012	Welcome to the new reality. @BarackObama is now letting China buy US banks http://t.co/i1C02ub2 The US government is selling us out.	1	-0.080
9-11-2012	China is an international pariah. They are now harassing Japan over its purchase of 3 uninhabited islands http://t.co/sPBPxwYY	1	-0.240
8-22-2012	It's Wednesday. I wonder how much money @BarackObama borrowed from China today?	1	-0.530
8-8-2012	No surprise that China was caught cheating in the Olympics. That's the Chinese M.O. - Lie Cheat & Steal in all international dealings.	1	-0.292
7-24-2012	China's domestic economic and political problems prove how pathetic our leadership is in allowing China to rip us off http://t.co/waPwJGxo	1	-0.098
6-26-2012	Scary–now China's Development Bank is looking to buy U.S. homes and developments http://t.co/Y50nOI5R They will own our country soon.	1	0.236
4-25-2012	"Right now we are running a massive \$300 billion trade deficit with China. That means every year. China is (cont) http://t.co/vcvETg5z	1	-0.014
1-12-2012	The US is always getting ripped off! China gets cheap oil from Iran and Iraq as US pays for Hormuz Patrols to (cont) http://t.co/J0QeWXy3	1	-0.102
12-19-2011	China just put a tariff on US cars and trucks–22%–China is laughing at our inept leaders. @BarackObama	1	-0.020
12-5-2011	We are building China's wealth by buying all their products even though we make better products in America.	1	0.330
9-21-2011	Our next President must stop China's Rip-off of America.	1	-0.443
8-16-2011	China owes us money.... http://t.co/ful8XAv #trumpvlog	1	0.164

Note: This table shows the event days, a sample tweet and the content-based categorisation and average sentiment for every group of pre-presidency tweets on the U.S.–China trade war.

Table A.5: Robust pre-presidency Content-Based categorisation

Content-Based categorisation pre-presidency							
Sector	Category	AAR					CAAR
		-2	-1	0	1	2	[-2,2]
Materials	1	0.0002	-0.0002	0.0005	0.0001	-0.0024*	-0.0015
IT	1	0.0003	-0.0014*	0.0014	-0.0011	-0.0018	-0.0028
Health Care	1	0.0002	-0.0002	0.0004	-0.0001	-0.0002	-0.0001
Consumer Staples	1	-0.0012	-0.0016**+	0.0000	0.0000	0.0010	-0.0017
Industrials	1	0.0007	0.0005	-0.0009	0.0010	0.0002	0.0016
Consumer Discretionary	1	-0.0002	-0.0003	0.0004	-0.0012	0.0017*	0.0004
Communication Services	1	0.0006	-0.0009	-0.0018	0.0010	0.0013	-0.0007
Energy	1	-0.0006	0.0004	-0.0025**+	0.0007	-0.0025	-0.0045
Financials	1	0.0008	0.0040***++	0.0005	0.0018*	0.0015	0.0090***+
Utilities	1	-0.0009	-0.0006	-0.0004	-0.0003	0.0022*+	0.0001
Real Estate	1	-0.0005	0.0021*+	0.0003	-0.0010	0.0002	0.0012

1 = escalating

t-test stat. sig. ** at 5% level * at 10% level : degrees of freedom = groupsincat-2

rank-test stat. sig. ++ at 5% level + at 10% level

Note: This table shows the AAR and CAAR of the event window for the pre-presidency content-based classification. Significance is evaluated using two-sided tests. Sectors are ranked from high to low exposure and defensive sectors are in bold font. This table used an estimation window length of 180-days.

Table A.6: Robust pre-presidency Sentiment by Polarity categorisation

Sentiment Analysis categorisation pre-presidency							
Sector	Category	AAR				CAAR	
		-2	-1	0	1	2	[-2,2]
Materials	0	-0.0016	-0.0005	-0.0005	0.0003	-0.0014	-0.0024
	1	0.0012	-0.0001	0.0008	0.0001	0.0030*	-0.0010
IT	0	0.0027**+	-0.0020	0.0007	-0.0004	-0.0032**+	-0.0027
	1	-0.0011	-0.0011	0.0018	-0.0015	-0.0010	0.0029
Health Care	0	0.0011	-0.0005	0.0003	-0.0005	0.0006	0.0006
	1	-0.0006	-0.0001	0.0005	0.0003	-0.0007	-0.0005
Consumer Staples	0	0.0008	0.0004	-0.0002	0.0008	0.0008	0.0036
	1	-0.0023*	-0.0029**+	0.0001	-0.0004	0.0010	-0.0045*
Industrials	0	-0.0005	-0.0004	-0.0011	0.0001	0.0001	-0.0015
	1	0.0014***+	0.0010	-0.0008	0.0015**+	0.0002	0.0033**
Consumer Discretionary	0	-0.0008	0.0003	0.0003	-0.0035***++	-0.0001	-0.0036
	1	0.0002	-0.0006	0.0004	0.0000	0.0026*	0.0026
Communication Services	0	0.0031	-0.0007	0.0017	0.0036+	0.0017	0.0077*
	1	-0.0009	-0.0010	-0.0038*+	-0.0003	0.0010	-0.0050
Energy	0	-0.0023	-0.0001	-0.0002	0.0013	-0.0016	-0.0027
	1	0.0004	0.0007	-0.0015*+	0.0003	-0.0029	-0.0054
Financials	0	-0.0022	0.0042**+	0.0006	0.0011	0.0034***+	-0.0067***+
	1	0.0025	0.0039***++	0.0005	0.0022	0.0005	0.0092***++
Utilities	0	-0.0041***++	-0.0005	0.0007	-0.0006	0.0032	-0.0009
	1	0.0009	-0.0006	-0.0010	-0.0002	0.0016	0.0007
Real Estate	0	-0.0026+	0.0026	-0.0010	-0.0035***++	0.0012	-0.0030
	1	0.0006	0.0018	0.0010	0.0004	-0.0003	0.0035

0 = negative and 1 = positive sentiment

t-test stat. sig. ** at 5% level * at 10% level: degrees of freedom = groupsincat-2

rank-test stat. sig. ++ at 5% level + at 10% level

Note: This table shows the AAR and CAAR of the event window for the pre-presidency sentiment-based classification. Significance is evaluated using two-sided tests. Sectors are ranked from high to low exposure and defensive sectors are in bold font. This table used an estimation window length of 180-days.