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The Cheerleader of The United States

The Effect of President Trump's Twitter on Consumer Confidence in the United States

By

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Abstract

How does Donald Trump's passionate Twitter usage impact consumer confidence? This paper develops a new time series measure of Donald Trump's Twitter based on a sentiment analysis using data from June 2016 to March 2018. Furthermore, we capture the economic sentiment based on computational text analysis using economic news articles from January 2000 to March 2018, assuming that Trump acts as an extension to traditional newspapers. Using these never deployed time series we are able to investigate how Trump can affect the Consumer Confidence Index in the United States, both on a national and regional level. This paper finds that Donald Trump has the ability to affect consumer confidence through his usage of Twitter. Observing stronger effects in regions that consist of mainly Republican constituents.

Keywords: Donald Trump, Consumer Confidence, Twitter, Sentiment, Text Analysis

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1. Introduction

The former real-estate developer and reality television personality, Donald J. Trump, was elected the 45th President of the United States in 2016. With no political experience and a controversial presidential approach, he took the nation by storm, winning against most pundits´ predictions. Due to his unusual rhetoric, political and social scientists have studied Trump's communication to understand how he won the presidential election. Using basic rhetorical tools, he appealed to the masses, transforming advanced political dilemmas into comprehensible ideas that most Americans could understand (Kayam, 2017). He was able to spread his oversimplified slogans in effective ways using modern day communication, with a possible winning edge in his extreme use of the social media platform, Twitter. Social media shaped the 2016 election in favor of Donald Trump, where a single tweet could drive media coverage and form political discussion like never before (Kapko, 2016). Whether it was a conscious strategy or a symbol of the period we live in, remains to be answered. Nevertheless, he made it work.

Rather than focusing on *how* Trump’s tweets helped him win the election, this paper studies whether his tweets have a broader impact on society. More specifically, we investigate if Trump's tweets *can* influence the public's perception of current and future economic conditions. In order to examine this effect, we will use the Consumer Confidence Index (CCI). This is a survey-based questionnaire which aims to capture consumers’ attitudes towards the economy, local job markets and their personal financial situation. These attitudes primarily build on information received through news media, where previous literature argues that media’s portrayal of changes in economic conditions can enhance the effect on consumers perception, relative to changes in economic reality (e.g. Soroka, 2006; Starr, 2012). Assuming that Donald Trump’s Twitter acts as an extension to traditional news media, the purpose of this paper is to investigate whether President Trump’s Twitter is able to affect consumer confidence.

To conduct this investigation, we examine monthly data from the Conference Board (CCI) and create a time series database that captures the tone in news articles covering the U.S. economy, using computational text analysis, between Jan 2000 – Mar 2018.[1] More importantly, we conduct a similar analysis of Trump’s Tweets, starting from when he won the Republican primaries in June 2016 (Bump, 2016). Through collecting more than 180 000 news articles from seven of the largest outlets and 4 500 tweets, we use these constructed time series variables to conduct a multiple regression analysis and investigate whether Trump has an effect on

[1] The media database developed in this study is available upon request.

consumer confidence. The main specification will study Trumps effect on a national level, while our alternative specification will explore whether there are any observable differences on a regional level. The idea is to investigate whether his effect is stronger in regions where he received an electoral majority in the 2016 election, as these areas to a higher extent support his personality or political agenda. In addition, we will build on previous literature in allowing for several macroeconomic indicators to affect consumer confidence.[2] In doing so, we investigate the robustness and predictive power of our models.

Our main contribution to this research field is split into two core parts. First, we construct two new databases consisting of President Trump's Tweets and news articles, that are subject to sentiment analysis following manual and computational approaches. Second, we include both these sentiments in the context of consumer confidence, accounting for the assumption that the former can act as an extension to the latter. Previous literature has studied the link to consumer confidence by both news media- and social media sentiment. Unlike these, we conduct an intersection between the two, with a primary focus on the effect of a single Twitter account.

The remainder of this thesis has the following disposition: Section 2 covers necessary background regarding consumer confidence, news, Donald Trump and relevant previous literature. A description of our data and the utilized method is thoroughly presented in section 3. Section 4 covers our results and interpretation while section 5 includes a relevant discussion. Our most important conclusions and some suggestions for future research are presented in section 6.

[2] General macroeconomic indicators (fundamentals) are e.g. GDP growth, unemployment rate, inflation rate, interest rate etc.

2. Background

This section starts with describing the growing interest and importance of the consumer confidence index among academics. Its ability to explain current and predict future macroeconomic conditions will be dissected and put into the context of news media. Through transmitting economic information that might affect consumers perceptions, it has often been linked to the consumer confidence index. Finally, the last section will provide an overview and description of Donald Trump. Given his personality, rhetoric's and use of Twitter, we aim to explain how he might be regarded as an extension to media, thus influencing consumer confidence.

2.1 Consumer Confidence and News Media Sentiment

Consumer confidence surveys have been conducted since the early 1940s in the United States. The purpose of these surveys and their constructed indexes are to capture and reflect consumers' attitudes towards current and future economic conditions (Frumkin, 2006, p.35).

The relevance of these indexes has retained much analysis since its introduction. Consumers' sentiments of optimism and pessimism regarding the economy have been closely linked to their perceptions of personal financial conditions and general business conditions. Following general economic theory, as consumers become more optimistic, their willingness-to-pay and spending increases, while saving decrease. Inevitably stimulating the economy. Certainly, as times worsen, consumers become more pessimistic, causing spending to decrease while the likelihood of saving and paying off debts increase (Frumkin, 2006, p.40).

Previous research conducted by Caroll et al. (1994), found that the consumer confidence index can explain future changes in consumer spending. Similarly, Huth et al. (1994) suggest that CCI can predict movements in variables such as the Dow Jones Industrial Average and unemployment rate. Further, Starr (2012) compare how CCI reacts to shocks in macroeconomic indicators, using a Structural VAR framework. Finding strong links to unemployment, interest rates, stock prices, inflation, and consumption. Implying that for example, a rise in stock prices causes increases in the CCI. Using similar economic fundamentals, Casey & Owen (2013) confirm several of these finding using a regression analysis approach.

Concluding that consumer sentiment is relevant to understand as a predictor of macroeconomic phenomenon's, it raises the question of what leads to changes in the CCI, starting with how consumers receive economic news. Most changes in the economy are not easily observable on a day-to-day basis, whereas newspapers and other media cover such areas. Newspapers have historically proven to be the primary source for delivering information regarding changes in the economy, thus having a crucial role in reflecting economic reality and forming the public's perception (e.g. Ioanăs & Stoica., 2014 Soroka, 2006).

The parallels between consumer confidence and media reporting have consequently inspired researchers to model and study the tone of news media in relation to CCI. Doms & Morin (2004) construct three different news sentiment indices and model their dynamics with CCI, controlling for several macroeconomic fundamentals. Following a Lexical computational approach, they construct their news media index by counting the amount of positive and negative keywords, in the headline or first paragraph of 30 large newspapers in the U.S. Their results reveal that economic reporting, both in tone and volume, affect consumer sentiment. Implying that as the tone becomes more positive (negative), consumers become increasingly optimistic (pessimistic) causing the index to rise (fall). Where their most striking result suggests that an increase in the volume of articles mentioning recession or layoffs, leads to a decline in sentiment. Shapiro et al. (2018) build on this, conducting an even deepened sentiment analysis, creating their indexes by breaking different articles into different emotions. Suggesting that news sentiment indexes highly correlate with both the consumer confidence index and macroeconomic indicators, especially for the federal funds rate and consumer price index. Further, they find that a positive news sentiment shock works in a similar fashion to an aggregate demand shock, increasing employment, inflation, and prices.

Soroka (2006) studied how asymmetric reactions affect the consumer confidence index, using data from Britain between 1986 to 2000. Following the autoregressive distributed lag approach (ARDL), he created a news sentiment analysis based on articles related to unemployment and inflation. The result showed that the public and the mass media responded much greater to negative economic news, rather than positive when being exposed to news of the same magnitude. In addition, the author suggested that mass media's response further enhances the public response, as the public reacts to both the mass media and the economy itself. Finally, showing that negative media content increases the public’s reaction to economic news by 16%. Starr (2012) finds similar effects, arguing that news shocks, defined as the instance when news media ‘overly’ exaggerate incoming economic data, to a large extent explain short-term fluctuations in CCI. Arguing that these types of shocks tend to spill over, increasing employment and boosting consumption. The general conclusion in both of these papers is that news media coverage is able to enhance the effect on consumer confidence, relative to changes in economic reality.

Over the last two decades, the reporting of news has been modernized and shifted from printed newspapers to digital editions, where social media has emerged as a central provider of news. According to recent findings, two out of three adult Americans retrieved their news through social media in 2017 (Shearer & Gottfried, 2018). Initially created as platforms where individuals connect with friends and people of similar interest, these have developed as being one’s primary source of information. This has led to a shift in focus towards the usability of social media messages, whereas several researchers have attempted to predict various stock markets using Twitter sentiment (Bollen et al., 2010; Rao & Strivastava, 2012). Further, the link between consumer confidence and general Twitter sentiment has been proved to exist. O´Connor et al. (2010) conducted a sentiment analysis in the U.S. using Twitter, through a word frequency count, arguing that social media is important to study since it might be regarded as an extension to traditional news media. When compared to CCI, they found a high correlation, suggesting that Twitter is important as it can capture large-scale trends.

Daas and Puts (2014) conducted a detailed analysis regarding the relationship between social media and consumer confidence. Through acquiring more than 3 billion social media posts, including Facebook, Twitter, LinkedIn, news sites and blogs, they were able to create individual and general social media sentiments. By comparing these with consumer confidence, they studied the correlation and lags of each social media platform. Their results show a very high correlation between consumer confidence and social media sentiment in general, in particular for the Twitter sentiment index that also displayed a seven-day lag. Arguing that the general Twitter sentiment reflects changes in consumer confidence after a week, but is observable prior to changes in consumer confidence data, as it's released the following month.

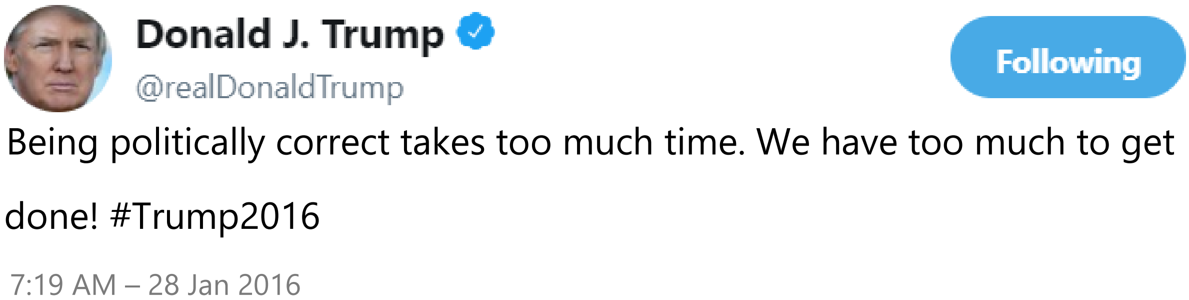
In conclusion, news- and social media has been proved highly important in influencing consumers’ perceptions of economic conditions. Modeling and understanding these perceptions is imperative to understand how they affect the current and future economy. Simultaneously, this also raises the question whether individuals can affect consumer sentiment through social media. What effects does an individual such as the President of the United States, Donald Trump, have on consumer confidence using Twitter?

2.2 Presidential Rhetoric and Donald J. Trump

Knowing the role of news media reporting in society and its effect on consumer confidence, we will now dive into the presidential role of delivering news, with our primary focus on Donald

Trump. Following, a presentation of the development of presidential rhetoric, an analysis of Trump's rhetoric and its applications to the social media platform Twitter, will follow.

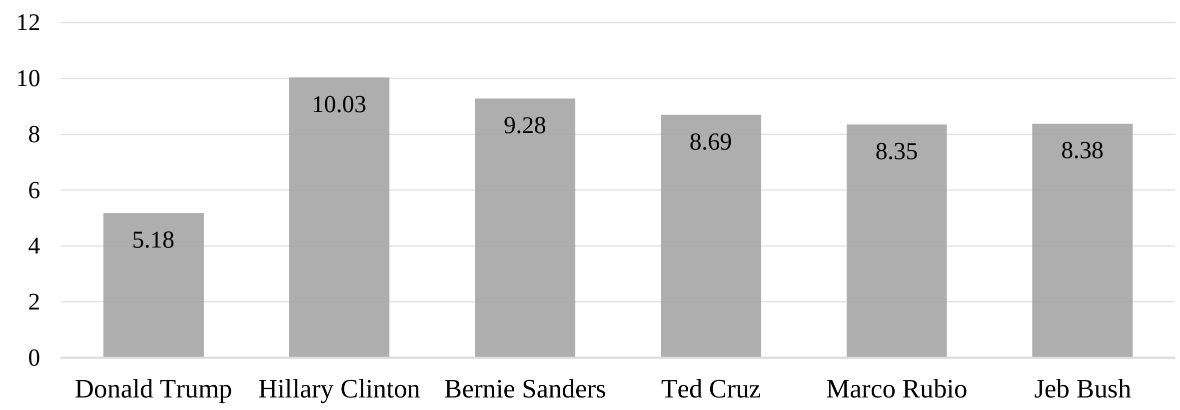
Political and social scientists have raised the issue of a growing culture of ignorance and anti-intellectualism in the U.S. Elvin Lim, professor in political science, argues that this development is increasing in presidential rhetoric, providing evidence for a constant linguistic simplification since 1789. The truncated structure in language leads to a development where the simplification becomes oversimplification in delivering adequate information to the public, as they seek to make competent civil judgments (Lim, 2008, p. 19). Other political scientists claim that the Republican party has worn a *know-nothing* façade for decades, in order to connect with ordinary Americans. Arguing that instead of fighting the anti-intellectualism they embraced it for their own political gain. They go as far as saying that the embrace of the anti-intellectualism was a put-on, at least until now (Boot, 2016; Raphael, 2016).



Donald Trump's presidential approach is both unorthodox and far from always politically correct, but he has proven to be a skilled rhetorician. Having good rhetorical skills is considered as being persuasive and convincing, which applies to politics as well, within the limits of stating rational and empirical arguments (Ross, 2015). Politicians have historically been somewhat restrictive in their statements, where one cannot say or promise whatever seems fit in order to win an argument (Krebs & Jackson, 2007). Donald Trump seldom follows these rules as he in many aspects differs from traditional politicians and particularly presidents. His language consists of repetition, exaggerated statements, a calm tone, simple grammar and vocabulary, where he frequently switches topic when he sees fit. Being closely related to how people speak on a regular basis (Inzauralde, 2017).

Political and social scientists have studied the language and style President Trump used during his campaign and presidency. The readability, simplicity, and straightforwardness of his language have been a much-discussed topic since the power of it was widely underestimated. In addition, being much darker, violent and filled with insults compared to any other politician (Ott, 2017). His rhetoric and visualization appealed to a broader share of the public than any poll or expert anticipated, through simply using big words and short sentences he created sticky phrases that everybody could understand (Kayam, 2017). Orly Kayam (2017) conducted a linguistic analysis of Donald Trump's language, using three different readability formulas she compares Donald Trump's language to his contenders. Following the approach of the Flesch-Kincaid readability test, the results presented in Figure 2.1 suggested that the average education required to understand Trump's language was at a fifth-grade level, equal to a 9 or 10-year-old.[3] Compared to his opponents, whose language was considered as far more advanced and required at least a ninth-grade level education, equal to a 14- or 15-year old (Kayam, 2017). Other research also points out the fact that when being exposed to ambiguous news, defined as news that consists of both a positive and a negative statement, people tend to become insecure, which eventually leads to negativity (Svensson et al, 2017). In Donald Trump's case, his short sentences and simple language eliminates this aspect which makes his communication very efficient and easy for voters to understand (Kayam, 2017).

Figure 2.1 – Illustrates the Flesh-Kincaid readability test for several presidential candidates



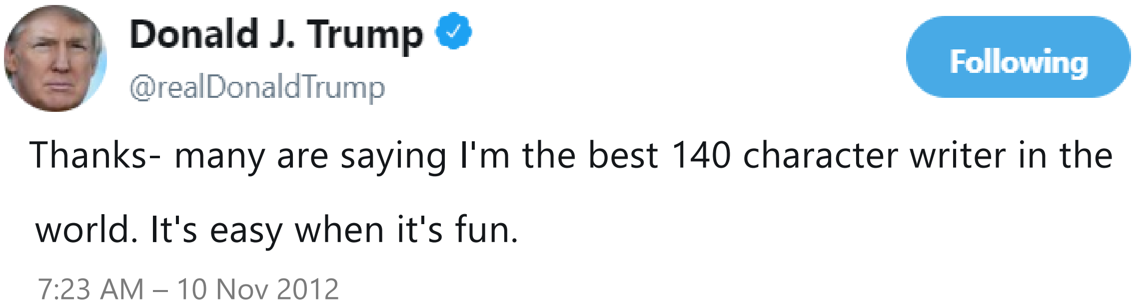
Source: Kayam (2017, p.82)

2.2.1 Twitter and @RealDonaldTrump

Researchers claim that he is a man of his times, like Franklin D. Roosevelt was to radio and John F. Kennedy was to television, Donald J. Trump is to Twitter (Gabler, 2016). Through a modern digital tool, he is able to create a direct line to the people, delivering a never-stopping stream of immediate updates and personal opinions. Comparing the way he expresses himself, and the way Twitter is set up, it is a perfect match (Ott, 2018). This microblogging-service

[3] The Flesch-Kincaid readability test uses linguistic text analysis to determine what level of education is required to understand the content of a text.

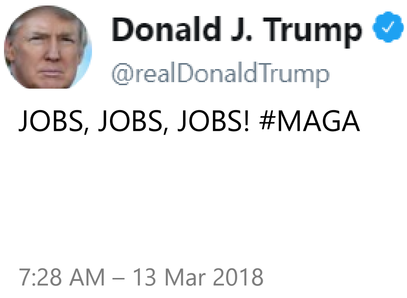
allows for instant messages up to 140 characters, more than enough for President Trump to express his simplified political statements or impulsive opinions (Carr, 2016).

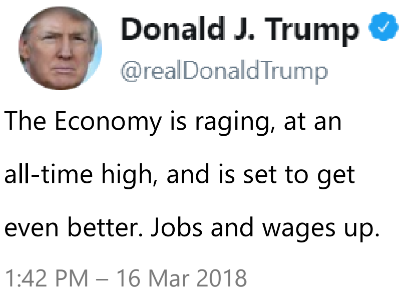


In earlier days, Donald Trump's personal Twitter account was barely concerned with politics. With a considerably lower number of followers, it was mainly used for personal promotion of TV-shows, books and general interests (Tsur et al, 2018). After Barack Obama took office he became more political in his tweets, with his first "Make America Great Again" tweet in 2012 (Carr, 2016). Following the announcement of his presidential candidacy in June 2015, his Twitter account accelerated in both followers and attention (Tsur et al, 2018). During this period, his account was primarily negative in sentiment, partially consisting of general criticism towards previous governments, nicknaming his opponents and branding the fake media. An analysis of his account before he was elected candidate for the Republican party, showed that 45 percent of his tweets were negative in sentiment, while only 28 percent were positive. More than 65 percent of his adjectives were used in a negative sentiment (Tsur et al, 2018). However, his sentiment has become increasingly positive after becoming the official nominee in July 2016, with an even more significant change after winning the election (Crocket, 2016) A fact that will retain much more focus in Section 3.3.

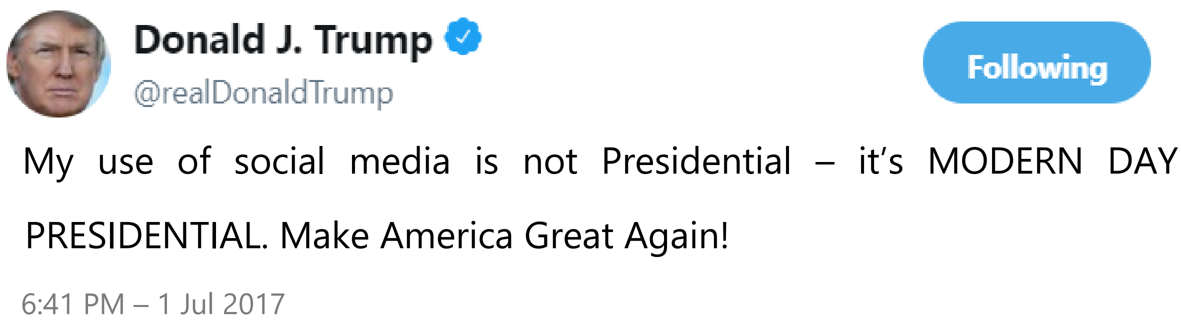
Today Trump's Twitter mainly consists of updates regarding the general economy, policies, travel plans, as well as comments on news media and articles. He has achieved more than 50 million followers, tweeting, on average, seven times per day, regularly obtaining several thousands of retweets. Surveys have found that three out of four Twitter users use this forum for gathering news, thus, it is not unreasonable to assume that Twitter is able to influence consumers similar to traditional news media (Newberry, 2018). In addition, many of Trump's tweets receive focus in various news outlets, extending his influential reach (Carr, 2018). Through tweeting updates and news concerning current and future economic conditions, consumers are able to use this information to form their perception of the economy. When posting positive tweets, such as the ones presented below, he is simply highlighting and strengthening positive economic news, while also enabling it to reach a bigger audience.

Repetition has been one of President Trump's most used rhetorical tools during his campaign and ongoing presidency, a common linguistic tool to strengthen a message or convince someone. By repeating favorable changes in macroeconomic indicators, he is reinforcing the idea of better economic conditions (Schulz-Hardt et al., 2016).





As for his negative tweets, there are almost seasonal fluctuations regarding his choice of topic, with a handful frequently recurring. General dissatisfaction of previous governments receives continuous criticism, with his main concern being their lacking ability to negotiate beneficial deals and focus on the American people (Wolf, 2018). Furthermore, a large fraction of his tweets are dedicated to the “fake media”. Whenever a media outlet expresses something he disapproves or that might be regarded as unfavorable towards him, he often jumps to Twitter and brands them as fake, dishonest or failing. Through attempting to weaken their credibility as trustworthy sources of information, he is somewhat trying to manipulate the public. Coll (2017) argued that his form of behavior is considered a strategy of distraction in times of controversy. Another highly unconventional side of his Twitter-usage is his bullying behavior with personal insults of celebrities, actors, presidential candidates and other national leaders. In his role as the President of the United States, much of his social media use could be regarded both morally and diplomatically wrong, but according to himself, he is only being modern.



When analyzing President Trump's tweets, it is clear that his negative tweets are rarely concerned with topics that portray the U.S. economy in an unfavorable way. Instead, these types of tweets contain information that is relatively insignificant to the average American when forming their attitudes towards the economic development. In the context of consumer confidence, his positive tweets are considerably more relevant in order to affect consumers perception about current and future economic conditions. The continuous hype and cheering for the U.S. economy started after he became president and has only been increasing. Further examined in Section 3., this is the main reason for his tremendous change in Twitter sentiment.

3. Data and Methodology

3.1 Consumer Confidence Index

This paper uses the consumer confidence index (CCI) produced by the Conference Board. Worth noting is that Michigan University (CSI) constructs a similar index following a different methodology. We chose the CCI as it is based on a survey sample of 5,000 questionnaires from different households, with a response rate around 60% each month (Conference Board, 2011). For comparison, the CSI consists of 500 interviews (University of Michigan, 2018). The difference in sample size and the fact that the Conference Board creates indexes for each of the country's nine Census regions, led us to this selection.

The Conference Board started collecting monthly data in 1977, with the purpose to capture consumers attitudes towards current and future economic conditions. Using a mail-based questionnaire, scheduled to arrive around the first of each month. The respondents are then asked to return their answer, preferably before the closing for preliminary results on the 18^{th}. Results are thereafter posted publicly on the last Tuesday of each month. The final results, consisting of the remaining completed questionnaires received after the 18^{th}, are presented together with the following month's figures (Conference Board, 2011). In addition, the Conference Board provides indexes for a handful states and nine Census regions. Furthermore, the respondents and their answers can be categorized based on household incomes and ages.

The Consumer Confidence Index is based on five questions divided into two parts, "present situation index" and "expectations index".

<u>Present Situation Index</u>

1. Respondents' appraisal of current business conditions.
2. Respondents´ appraisal of current employment conditions

<u>Expectations Index</u>

3. Respondents´ expectations regarding business conditions for the next six months.
4. Respondents´ expectations regarding employment conditions for the next six months.
5. Respondents´ expectations regarding their total family income for the next six months.

For each question, there are three possible answers; “positive”, “neutral” or “negative”. By taking the positive answers divided by the sum of positive and negative answers, they create an index of relative scores. The questions are then converted into a consumer confidence index (average of all questions), present situation index (average of question 1 and 2) and expectations index (average of question 3, 4 and 5) (Conference Board, 2011).

Given the interest in studying whether there exist observable differences of Trump’s effect on consumer confidence amongst regions, we used a corresponding index for each of the country’s nine Census regions provided by The Conference Board. These are groupings of states that subdivide the United States, developed by the Census Bureau, a government agency that collects and present data about the nation’s people and economy (Census Bureau, 2015). In an attempt to map the political landscape of these regions we use the latest election results from 2016. Using electoral votes, we are able to categorize all regions as mainly Republican or Democrats.[4]

3.2 News Sentiment Analysis

In modern years computational text analysis has become increasingly common when conducting sentiment analysis. Compared to previous survey-based analysis, this is now generally preferred due to being less costly and time-consuming, as well as allowing for analysis of much larger samples (Laughran & McDonald, 2011). There are two main approaches available to computational analysis, one of which being the Lexical model. This is a word frequency model, where the researcher uses a predefined dictionary, consisting of words which are connected to a polarity score.[5] Following this approach, one can retrieve the sentiment of an individual article, where repetition of this process for a large data sample creates a time series. This model is considered as fairly naive as it does not consider the full context of a sentence or text. In addition, researchers have also pointed out that these predefined dictionaries should be adjusted to the content of the text being analyzed, as polarity scores for single words may differ in different contexts (Khalifa & Omar, 2014; Laughran & McDonald, 2011). Our news sentiment is constructed using an alternative, more sophisticated approach; the Natural Language Processing (NLP) method, which will retain much focus in this section.

Before conducting the textual analysis, we were required to find and download a large set of news articles. Given that this paper aims to capture if Trump’s Twitter and news media can

[4] A graphical presentation of these regions and their political landscapes through presidential elections from 2000, is available to the curious reader in Appendix I.
[5] Polarity score is the score a word receives for being either negative, neutral or positive.

affect CCI, we only focused on articles that are economy-related. The sample size consisted of the largest available newspapers from the United States between January 2000 and March 2018. The two search-engines used to retrieve the data were LexisNexis Academic and ProQuest, where the user can apply relevant limitations. We were able to retrieve 182 891 news articles from seven different news outlets, summarized in Table 3.1.

LexisNexis Academic provides full-text access to more than 15.000 international news, business and legal sources. Through their search engine, we were able to collect articles from New York Times, USA Today, The Mercury News, New York Post, The Washington Post and the Atlanta Journal-Constitution. In order to retrieve articles from the Wall Street Journal, we were forced to use ProQuest, which is a similar search engine. Using their Power Search and Advanced search functions, we applied the following search limitations to each newspaper:

(1) Topic Subject: “economic”, “economy”, “consumer confidence”, “unemployment rate” and “interest rate”. (with an 85 percent relevance threshold)
(2) Country Subject: “The United States” (with an 85 percent relevance threshold)
(3) Articles containing at least 200 words.
(4) “Web-based newspapers” and “Newspapers”
(5) Topic Subject NOT: “sport”
(6) Headline NOT: “paid notice”, “treasury auctions”, “residential sales”.

The words “economic”, “economy” and “consumer confidence” are highly relevant and broad search terms. Furthermore, we included “unemployment rate” and “interest rate” into our search as these are macroeconomic indicators that potentially affect consumer sentiment. This methodology is similar to previous work conducted by Doms & Morin (2004) and Shapiro et al. (2018). In addition, after analyzing the search results we observed a few irrelevant articles. To adjust this and exclude these types of articles we added a few topics and headline limitations, as indicated by the two final restrictions.

Table 3.1 Overview of our dataset containing articles from different news outlets

Newspaper	# of articles	Share (%)	Circulation[i]	Source
New York Times	46 484	25.4	730 386	LexisNexis
Wall Street Journal	32 479	17.8	731 266	ProQuest
Washington Post	32 477	17.8	546 810	LexisNexis
Mercury News	25 772	14.1	582 411[ii]	LexisNexis
Atlanta Journal	23 762	13.0	285 705	LexisNexis
USA Today	13 877	7.6	2 778 243	LexisNexis
New York Post	8 040	4.4	400 724	LexisNexis
	182 891	100		

[i] Data regarding circulation was gathered from Audit Media (database via email, 3 April 2018)
[ii] Report of circulation was from Q3 2017 and not Q4 2017, as it was not yet released.

It is relevant to mention that due to the enormous data-sample, we were not able to control all articles to determine their relevancy. Using our restrictions, we tried minimizing the aspect of including irrelevant articles. Attempting various amounts of restrictions and limitations, we found this as the best methodology. We did not believe that this would endanger our further analysis as we have used relevant words that are similar to previous research (Doms & Morin, 2004; Shapiro et al., 2018). Through our examination of different samples within the search result, it became evident that our selected criterions were both relevant and effective.

Following the highly computational approach of Natural Language Processing (NLP), we could conduct our sentiment analysis of these articles. This is a supervised machine learning methodology, which implies that the researcher must create code that allows the computer to analyze, understand and derive the meaning from human textual language (Olah, 2015). This process usually requires already created datasets, so-called labeled data. Labeled in this context means that words, sentences, and general texts have received an interpretation categorized as either *positive*, *neutral* or *negative*. Given that our sample consists of economic news articles, we searched for such a labeled dataset. After extensive research, we found a few small datasets that could be considered as applicable to our sought methodology. These were mainly developed towards the Lexical, bag of words, framework. As this was not our desired approach, we were forced to search for other alternatives. Instead, we used *transfer learning* and trained our model on a dataset containing 50 000 IMDb movie reviews (Maas et al., 2011). [6] This

[6] Transfer learning is the process of training a model on a similar dataset, before transferring the final model back to the intended dataset.

labeled dataset is the most extensive available within this field, containing graphic language that naturally contains a sentiment which can be subject to meticulous classification by humans. There is a balance between choosing a small dataset or an extensive dataset used from another subject. In order to test the effectiveness of our chosen method, we tested both approaches. Where our selected method was far superior, compared to the Lexical approach, in producing a sentiment analysis that resembled previous research. As our resulting time series graph will demonstrate, the sentiment analysis proved to some extent follow the CCI, which is similar to previous research (Shapiro, 2018; Starr, 2012). Combined, these arguments made us confident in that our selected method is the most appropriate method available.

After downloading the labeled dataset of IMDb articles, we started by *tokenizing* each news article, so that the words from the texts could be subject for further analysis. For example, a sentence such as:

Fake media is working overtime today. Drain the swamp.

was be tokenized into:

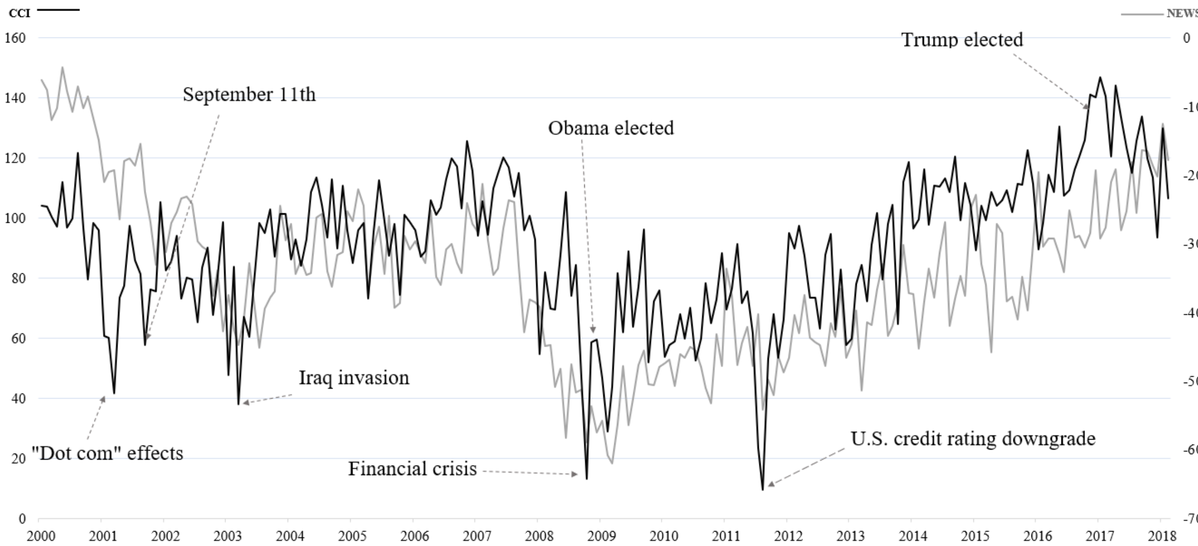
'Fake', 'media', 'is', 'working', 'overtime', 'today' 'Drain', 'the', 'swamp'

Following this process, the model uses the information it has from the IMBD articles in analyzing, understanding and deriving the meaning of a text. Further, as the model continues to go through articles it picks up new knowledge and identifies new words that are then labeled as either positive or negative. Thus, improving and recalibrating the model itself. Based on combination, structure, and choice of words, the model is able to extract the emotional content of each article and then create a sentiment score (Shapiro et al., 2018).

Initially, the network creates an analysis with a singular output node. This means that the output will be in the form $[0, 1]$, where 0 is negative and 1 is positive. However, as we aim to create comparable results with the sentiment analysis of Trump's Twitter, the network was recalibrated and trained over two output nodes, yielding identical results. Such a network would have one node outputting a probability, p, that the text is positive, and a second node which would output the probability, $1 - p$, that the text is negative. This format is far more practical to visualize on a positive and negative scale, and as such we have for analytical reasons chosen to rescale the output interval from $[0, 1]$ to $[-1, 1]$ (Olah, 2015). Furthermore, we have chosen to set articles classified between $-0{,}1 < x < 0.1$ as neutral. This is done as the results would otherwise be impaled by texts which the model merely guessed on. In total, we marked $\sim 5\%$ of the texts as neutral using this method.

In creating the final sentiment score and the time series, we sum all the sentiments for each respective newspaper and create an average. The individual scores of each article are thus bounded $[-1,1]$, whereas the total average is unbounded.

Figure 3.1 Illustrates the Consumer Confidence Index and News Sentiment



Conducting graphical analysis of our news sentiment, we conclude that our news media sentiment is consistently negative which is in line with previous literature (Shapiro et al., 2018; Starr, 2012). This might be explained by the fact that 61 percent of our articles are categorized as negative in sentiment, while only 34 percent are positive. We interpret this as an indication of a negativity bias within the newspapers. There are two main explanations for this, one being the fact that journalists suffer the same negativity bias as consumers. The other being based on economic theory, where newspapers try to maximize their profit, hence choose to print stories that attract the most buyers. Negative stories are historically the ones making headlines since they draw the most attention (Casey and Owen, 2013). Graphically we can observe that our news sentiment to some extent follows the movements of the consumer confidence index. Further, we observe clear positives and negative shocks around certain economic or political events, outlined in the graph.

Table 3.2 *Polarity of news articles*

Positive	61 795	34 %
Negative	111 577	61 %
Neutral	9 519	5 %
Total	182 891	100 %

3.3 Trump's Twitter Sentiment Analysis

We have constructed our own Donald Trump Twitter sentiment variable using a website which allows users to search and download tweets produced by Donald Trump (Trumps Twitter Archive, 2018). In our selected time-period, from June 2016 to March 2018, we downloaded

4,490 tweets made by Trump's personal Twitter account. We chose these dates since the race for the Republican presidential nomination was considered over by the end of May 2016, as he had clinched the sufficient number of party delegates required (Bump, 2016). To perhaps capture the true effect of his Twitter on CCI, it would have been more valuable to start the study from when he entered office, January 2017. However, this would imply that our sample would only contain 14 observations which is relatively small. As we wished to include as many observations as possible, we increased the studied timespan until our selected period. We argue that even though he was not president at that time, he was still regarded as the presidential candidate of the Republican party with vast public influence.

In creating our monthly sentiment score, we categorized tweets as positive, negative or neutral. When considering a tweet as positive it received the value of 1, while neutral and negative tweet were classified as 0 and -1, respectively. Following this procedure, we manually categorized each individual tweet and generated a monthly sentiment score using the already developed formula presented below:

$$\pi_t = \frac{\sum p_t - \sum n_t}{\sum p_t + \sum n_t} \tag{3.1}$$

The sentiment, π at time t is equal to the sum of positive tweets minus the sum of negative tweets, divided by the sum of both tweets combined (Fraiberger, 2016; Soroka et al, 2015).

Below we provide examples of categorized tweets:

Table 3.3 Examples of tweets categorized as positive (1)

(1)	"New Q poll out- we are going to win the whole deal- and MAKE AMERICA GREAT AGAIN! #Trump2016" (2016-06-29)
(2)	"Buy American & hire American are the principals at the core of my agenda, which is: JOBS, JOBS, JOBS! Thank you @exxonmobil." (2017-03-06)
(3)	"Manufacturing growing at the fastest pace in almost two decades!" (2018-03-01)

Table 3.4 Examples of tweets categorized as negative (-1)

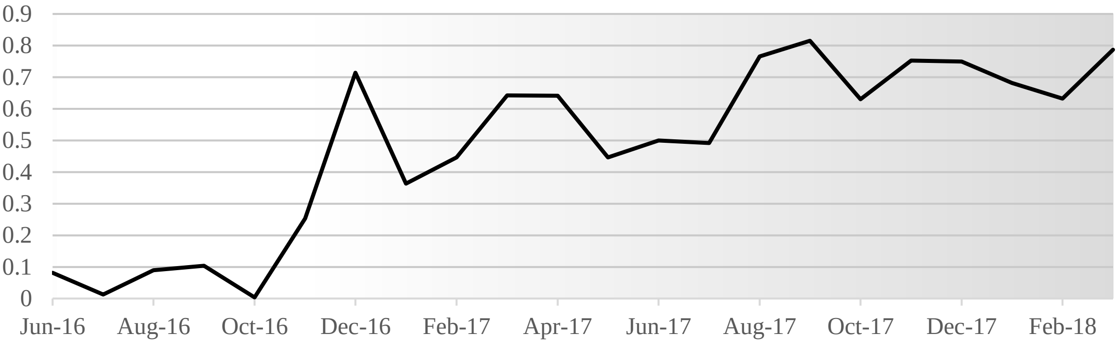
1. "The @USCHAMBER must fight harder for the American worker. China and many others are taking advantage of U.S. with our terrible trade pacts" (2016-06-29)
2. "For eight years Russia "ran over" President Obama, got stronger and stronger, picked-off Crimea and added missiles. Weak! @foxandfriends" (2017-03-07)
3 "The Russia hoax continues, now it's ads on Facebook. What about the totally biased and dishonest Media coverage in favor of Crooked Hillary?" (2017-09-22)

In order to create a consistent categorizing procedure, we initially read through an extensive number of tweets and discussed their individual sentiment. In doing so, we recognized that some tweets are simple announcements of him attending or thanking different events, television programs or cities/states. Furthermore, congratulatory or condoling messages and slandering of actors or other personalities were also identified. Tweets dealing with these topics were excluded from the sentiment analysis and received a neutral score as these contain information that is considered irrelevant in forming consumers attitudes towards the economy. Next, both authors of this paper individually read through all tweets and then compared the scores. In those cases where we observed a difference in categorization, we processed the tweet once more and reached an equilibrium in what sentiment score the tweet should receive.

It is relevant to highlight that the construction of this variable has a few short-comings. In evaluating each tweet there is naturally some exposure to personal interpretations and biases, regardless of our intention of being as neutral as possible. Optimally we would have desired to run all tweets through a large number of individuals in order to minimize the risk of personal biases and potential flaws. However, this was not an option within the limits of this thesis and instead, we developed the above-mentioned strategy which we considered as the optimal approach. Given that we created a framework and then reviewed all tweets individually to later compare all deviations, we consider the risk of having inconsistent data as small.

In addition, there is a risk of processing errors which occur during the process of data collection and data entry. During the process of categorizing the tweets gathered from TTA, we identified gaps in our timeline, where dates were missing. These were then collected manually through his twitter account. Thus, there might exist additional dates or tweets that might be missing. Nevertheless, we consider the number of tweets possibly missing as small, and that the sample of 4,500 tweets is more than enough to capture the general sentiment in his twitter.

Figure 3.2 Illustrates Donald Trump's Twitter sentiment.



The resulting monthly sentiment scores are presented in figure 3.2. We conclude that our data consists of 2517 positive, 1056 neutral and 917 negative tweets. An interesting observation is that his Twitter sentiment before he was elected as president (8th November 2016) was slightly positive, in comparison with the preceding months. There exists a clear break from this month, reaching a peak in December, where he became increasingly positive as he was president-elect and subsequently president.

3.4 Control Variables

Unemployment rate (UR) - Through the Bureau of Labor Statistics, we downloaded monthly seasonally adjusted unemployment rates dating back to January 2000 (Bureau of Labor Statistics, 2018).

Federal Funds Rate (FED) - The Federal Funds rate is the interest rate which banks can lend reserve balances to other banks, it is considered one of the most important interest rates in the U.S. Downloaded via Thomson Reuters and not seasonally adjusted (DataStream, 2018a).

Dow Jones Industrial Average (DJIA) – This index consists of thirty major stocks being traded on the Nasdaq and New York Stock Exchange. Downloaded via Thomson Reuters, not being seasonally adjusted (DataStream, 2018b).

Gas prices (GAS) – Due to the fact that many individuals frequently purchase gas, it can be a significant expense for many households. Being readily observable, we collect monthly data of an index produced by the Bureau of Labor Statistics, not being seasonally adjusted (DataStream, 2018c).

Consumer price index (CPI) - The consumer price index is a measurement that evaluates the prices of a basket of consumer goods and services. It can be compared to *cost of living* and is often used as an indicator for identifying inflation or deflation over certain periods of time. This data is seasonally adjusted and downloaded via Thomson Reuters (DataStream, 2018d).

3.5 Regression- and Data Analysis

The effect of Trump on consumer confidence is modeled using several regression models. The main specification will study the national index, where all states are pooled into one. We will allow for at most three lags in all variables in this model, with the main variables of interest being; CCI, TRUMP, and NEWS. Since using the lagged values of CCI adds explanatory power to the model, these will be used. To investigate the robustness and consistency in our results, we will allow for different macroeconomic indicators serving as control variables. The alternative, regional specification, will explore whether there exist any differences between regions when studying Trump's effect on the consumer confidence index.

When implementing these control variables, we will limit the study by allowing for at most one lag. This delimitation and the different lag-orders selected for the different variables follows previous research that is built on economic intuition (Casey and Owen, 2013; Guelly and Sultan, 1998; Starr, 2012). For example, when information about the unemployment rate is published, it represents the previous month, thus there exists a natural lag. For further deepened description the reader is referred to the mentioned literature, as this does not affect the general outcome of this paper.

Due to its universal and comprehensive use, a complete statistical decomposition of regression theory won't be presented, instead, the reader is encouraged to study relevant literature (e.g. Verbeek, 2004). In the use of time series data, there are several aspects that need to be investigated and accounted for in order to retrieve robust results, primarily stationarity. Displayed in Table 3.5, we conducted the Dickey-Fuller (DF) test for a unit root.

Table 3.5 Dickey-Fuller Unit Root Test

	Levels		First Differences	
	No Trend	Trend	No Trend	Trend
CCI	-3.984*	-3.851*	N/A	N/A
NEWS	-5.717*	-6.124*	N/A	N/A
TRUMP	-2.082	-3.761*	-6.262*	-6.153*
UR	-0.725	-0.064	-11.331*	-11.669*
CPI	-1.035	-1.598	-9.286*	-9.284*
FED	-1.999	-0.563	-6.034*	-6.192*
DJIA	1.271	-0.961	-13.99*	-14.212*
GAS	-1.952	-1.891	-8.953*	-8.946*

* Indicates rejection of the null hypothesis of nonstationary at the 5 percent level

In the case of CCI and NEWS, the test is able to reject the null hypothesis of a unit root, implying that these variables are stationary, thus treated in their level.

Interestingly, we observe that the test yield contradicting results for Trump's Twitter sentiment. Deemed as non-stationary without a trend, while being stationary with a trend. Graphical analysis of this variable, Figure 3.2, exhibits clear evidence of a structural break in November 2016. Perron (1989) found that when conducting unit root tests in the presence of a structural break, contradicting results are not uncommon. This adds the risk of a researcher deeming a series as non-stationary when it is in fact stationary. Furthermore, others argue that unit root tests can be seriously misleading, causing researchers to make incorrect conclusions (Leybourne et al., 1998). In addition to containing a structural break, TRUMP is a bounded time series between $[-1, 1]$. Researchers have found that when dealing with these types of series, one should always be cautious when the null hypothesis of a unit root is rejected (Cavaliere, 2005). Where it is not possible to determine if the rejection of the null is due to the fact of the presence of bounds or the absence of a unit root. Concluding that the rejection of non-stationarity might be a direct consequence of the series being bounded, and not because of stationarity (Cavaliere & Xu, 2014).

This raises the question whether the TRUMP series is in fact bounded stationary with a structural break or not. Being aware of the implications of conducting regressions on non-stationary data (spurious results or inference), we deemed this variable as stationary. Given the previous findings when conducting a DF-test when a time series exhibits structural breaks and bounds, we deemed it reasonable to make the assumption of stationarity. Furthermore, conducting two separate DF-tests, allowing for a structural break in November 2016, the test showed that that the series is in fact stationary, as seen in Table 3.6.

Table 3.6 Dickey-Fuller Unit Root Test with a structural break.

	BEFORE NOV 2016		AFTER NOV 2016	
	No Trend	Trend	No Trend	Trend
TRUMP	-3.505*	-6.249*	-3.615*	-4.393*
Observations	5		17	

* Indicates rejection of the null hypothesis of nonstationary at the 5 percent level

In conclusion, we will treat this variable as stationary with a structural break. To account for this break, we will add a dummy variable for November 2016 in our conducted regressions. Furthermore, building on previous research we will add a structural break for September 2001, the month of the September 11 attacks (Casey and Owen, 2013; Starr, 2012). To account for the economic crisis that erupted in 2008, we will add a dummy variable for October of that year. This is the first month after the bankruptcy of Lehman Brothers, an event that to a great extent affected the CCI. Furthermore, it caused the largest decline in the Dow Jones Industrial Average since the September 11, 2001, attacks (Kiersz, 2018).

Another common property in time series data is autocorrelation. To measure the degree of serial correlation the Ljung-Box Q statistics are computed for the first 24 lags of each variable. The results of the test are reported in Table 3.7, indicating that the null hypothesis of no autocorrelation can be rejected at the 5 percent significance level for all our variables. Seeing that autocorrelation is present in our series, we use Newey-West (robust) standard errors to correct for this, known as heteroscedastic-and-autocorrelation-consistent (Verbeek, 2004, p.111).

Table 3.7 Summary Statistics

	Obs.	Mean	*SD*	Min	Max	Q (24)	Order
CCI	219	81.632	27.391	18.300	150.300	1597.34*	I (0)
NEWS	219	-30.288	10.592	-65.924	- 5.744	963.85*	I (0)
TRUMP	22	0.050	0.170	0.000	0.815	N/A [i]	I (0)
UR	219	6.086	1.763	3.800	10.000		
Δ ln UR	218	0.000	0.027	-0.063	0.077	150.05*	I (1)
CPI	219	211.657	23.521	169.300	249.619		
Δ ln CPI	218	0.002	0.003	-0.018	0.014	69.58*	I (1)
FED	219	1.756	2.003	0.070	6.540		
Δ ln FED	218	-0.006	0.154	-0.911	0.693	77.52*	I (1)
DJIA	219	12933.100	3909.061	7062.930	26149.390		
Δ ln DJIA	218	0.004	0.041	-0.152	0.101	37.93*	I (1)
GAS	219	214.139	66.611	95.401	347.357		
Δ ln GAS	218	0.003	0.066	-0.369	0.160	115.11*	I (1)

* Significant at the 5% level.

[i] This variable only has 22 observations, while the Ljung-Box test requires 24 lags.

Furthermore, we are concerned that our results might be influenced by multicollinearity, suggesting that two or more variables in the model have high correlation (Verbeek, 2004, p.42). In order to verify that multicollinearity is not present in our results, we calculated the variance inflation factor for each of the coefficients retrieved. The rule of thumb used by most researchers implies that the variance inflation factor should be below 5 or 10 (Casey & Owen, 2013). The resulting analysis showed that for each coefficient estimated, the variance inflation factor was below 5. Thus, we conclude that our results are not influenced by multicollinearity.

4. Results

Familiar with the background of our method and variables, we will now present our empirical results found through the multiple regression analysis. The results will be split into two sections, where the first section, 4.1, presents the general model which studies the effect Trump and News have on CCI. In order to test the strength of our model, we allow for five macroeconomic fundamentals to act as control variables. Section, 4.2, explores whether there exist differences between regions.

4.1 General Analysis

Table 4.1 reports results from our investigation. In the first column, we start by constructing a highly primitive specification which does not include any control variables nor lags. We observe that Donald Trump has a positive significant effect on CCI, through his use of Twitter. More specifically, a 0.1-point increase in Trump's Twitter sentiment causes a 4.6 increase in CCI. Furthermore, news media displays a similar positive relationship which is in line with previous research (Casey and Owen; 2013; Doms & Morin, 2004; Soroka, 2006).

Table 4.1: The impact of Donald Trump's Twitter on the Consumer Confidence Index – U.S.

	1	2	3	4	5	6
TRUMP	46.028***	19.749***	15.929***	14.783***	16.968	12.494
	(5.473)	(5.560)	(5.731)	(5.584)	(16.026)	(14.262)
TRUMP (1 lag)					1.870	0.960
					(17.987)	(15.842)
NEWS	1.081**	0.506***	0.460***	0.433***	0.359***	0.301**
	(0.099)	(0.108)	(0.103)	(0.105)	(0.126)	(0.122)
NEWS (1 lag)					0.290**	0.263**
					(0.117)	(0.108)
CCI (1 lag)		0.584***	0.444***	0.413***	0.543***	0.384***
		(0.060)	(0.068)	(0.068)	(0.060)	(0.069)
CCI (2 lags)			0.213***	0.137*		0.122*
			(0.065)	(0.072)		(0.070)
CCI (3 lags)				0.149**		0.153**
				(0.068)		(0.067)
Adj R^2	0.698	0.804	0.808	0.809	0.807	0.811
AIC	1814.02	1708.39	1692.59	1682.25	1706.352	1681.02
BIC	1830.96	1728.70	1716.25	1709.25	1733.428	1714.78

Note: Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

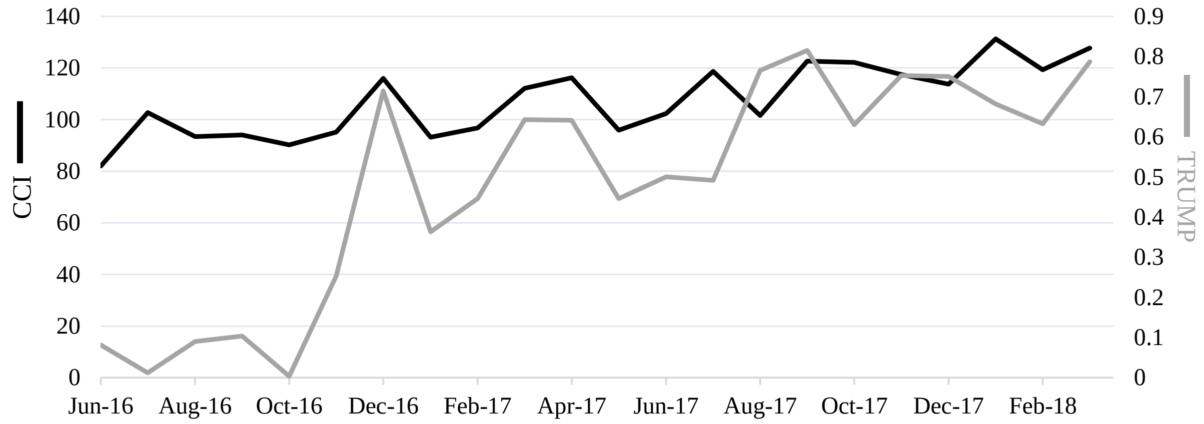
Looking at column 2, we see that including the lagged value of CCI increases the overall predictive ability of the model in terms of lower AIC- and BIC statistics. This is not surprising as including its own lag adds explanatory power to the model. Comparing the coefficients to the previously obtained values, we conclude that they decrease substantially for NEWS and TRUMP. This is particularly interesting for the latter variable as it implies that President Trump has a small effect on consumer confidence. In this model, a 0.1-point increase in his Twitter sentiment increases CCI with 1.98 points. Such an increase in his overall sentiment can be considered as relatively large as it is bounded between $[-1,1]$. In addition, from our graphical analysis presented in section 3.2, his sentiment has consistently been between 0.4 – 0.8 since winning the election.

Adding additional lags of CCI, conducted in column 3 and 4, we similarly observe that the effect of Trumps Twitter sentiment becomes increasingly smaller. Where a 0.1-point increase causes CCI to increase by 1.48 units. Furthermore, the model continues to gain predictive ability as shown by the increasingly smaller AIC- and BIC statistics, where the fourth model has the smallest value across all our specifications. This fact is relevant as we move to the regional analysis presented in the subsequent section.

In an attempt to investigate whether Trumps effect extends, and possibly displays some lagging behavior, we conduct such an analysis as shown in the fifth and sixth column. The analysis concluded that this type of lagging behavior does not exist in his Twitter sentiment, in relation to CCI. Suggesting that he only has coincident effects, which are shown to be significant. This further strengthens the idea that his Twitter only affects consumers within the same month. However, we can identify a lagging effect in news to CCI which is in line with previous research (Starr, 2012; Daas & Puts, 2014; Soroka, 2006).

Further investigation of this result using Figure 4.1, supports that it is not surprising that his sentiment in many instances follows CCI. For example, in January 2016 his Twitter sentiment had decreased compared to the previous month, as had CCI. This was then followed by a three months period of increases in CCI. Certainly, there are other factors contributing to the explanation of these similarities in movements. Nonetheless, observing how an increase in his sentiment is related to an increase in CCI, given data and graphical analysis, we are confident in making the conclusion that Trump effects CCI.

Figure 4.1 Illustrates the Consumer Confidence Index and Trump's Twitter sentiment



Naturally, the strength of our models is to be questioned. To investigate the robustness of our specifications we allowed for different macroeconomic indicators to serve as control variables. The results of this analysis are presented in Appendix II, as the main purpose is to test whether we observe any abnormal deviations in our previously obtained results, potentially questioning its statistical significance. Observing Table A.2, we conclude that the coefficients are similar to the ones found before when controlling for macroeconomic indicators. Naturally, there exist minor variations in how substantial the TRUMP effect is on CCI, however, in unison with previous results; the effect remains considerably small. Further analysis of these results indicates that the relationships of these variables to CCI are in line with previous literature (Casey and Owen, 2013; Soroka, 2006; Starr, 2012). Where the UR, GAS, and CPI has a negative relationship to CCI, which follows the general framework since these types of indicators are deemed as counter-cyclical (Chen, 2011). Lastly, DJIA and FED display a pro-cyclical behavior which also is in line with previous literature (Casey and Owen, 2013). The fact that the Federal Funds interest rate increases as CCI increases might seem surprising at first glance. However, previous research has found that this indicator is lagging to consumers' confidence, as the Federal Funds Board responds to increased positivity in consumers by increasing the interest rates (Doms & Morin, 2004; Starr, 2012). Thus, concluding that this positive relationship follows economic intuition, where increased consumer confidence causes the Federal Reserve to increase its interest rate.

In summary, our results suggest that Trump has a small, yet significant effect on consumer confidence.

4.2 Regional Analysis

This section will explore whether there exist any differences between regions when studying Trumps effect on the consumer confidence index, for the respective regions. Thus, instead of studying the CCI for the entire country as our dependent variable, we will now look at each separate region and its corresponding CCI, holding our explanatory variables unchanged. When presenting the results in this section, we only display the model with the lowest BIC value from the preceding section; model 4. Additional models that support the results presented in this section are found in Table A.3.

Our results, presented in Table 4.2, establish that there exist differences in the magnitude of Trump's Twitter effect between the different regions. The strongest effect is found in East South Central, where a 0.1-point increase in TRUMPS Twitter sentiment is found to increase CCI in that region by 1.97 points. This region consists of four different states; Alabama, Kentucky, Mississippi, and Tennessee, which have all been known as so-called Red states in every election since 2000 (Figure A.2). The effect of his Twitter sentiment is higher in this region compared to the national effect found in the general model previously presented, recalling the effect being 1.48 points. Further, we find consistent evidence that Trump has an effect in East North Central. This result is a striking feature, as further investigation of the history in recent elections, using Figure A.2, reveals that this region consists of several swing states. However, in the recent election, this region was dominated by Republican constituents, which to some degree might be due to Donald Trump and his Twitter usage.

Furthermore, we observe that Trump has an effect on states that primarily consist of Democratic constituents. For example, the state's New York, New Jersey and Pennsylvania have been dominated by the Democrats since the presidential elections of 2000, making up the Census Region Middle Atlantic. Thus, it is not surprising that we observe a lower effect of his Twitter in this region using our analysis. The general effect is found to be smaller in regions consisting of Democratic constituents, compared to regions where the Republican party has stronger support. A result that we found across further specifications, which can be found in Table A.3. Conducting a similar robustness check as in the general model, using economic fundamentals as control variables, Table A.4, we conclude that our results are consistent. While we only observe smaller differences in coefficients and significance, the general outcome of our analysis remains intact.

Table 4.2 The impact of Donald Trump's Twitter on the Consumer Confidence Index, across nine Census Regions.

	East North Central (R)	West North Central (R)	South Atlantic (R)	East South Central (R)	West South Central (R)	New England (D)	Middle Atlantic (D)	Pacific (D)	Mountain (N)
TRUMP	10.966**	11.016*	6.546	19.727***	7.006	7.119**	7.442**	5.205	7.702
	(4.215)	(4.580)	(3.996)	(6.842)	(4.527)	(5.725)	(3.715)	(3.392)	(5.304)
NEWS	0.237***	0.359***	0.339***	0.404***	0.290***	0.411***	0.325***	0.372***	0.536***
	(0.062)	(0.079)	(0.074)	(0.089)	(0.066)	(0.102)	(0.059)	(0.071)	(0.097)
CCI (1 lag)	0.687***	0.368***	0.673***	0.365***	0.566***	0.425***	0.515***	0.571***	0.458***
	(0.060)	(0.072)	(0.069)	(0.060)	(0.079)	(0.067)	(0.073)	(0.073)	(0.064)
CCI (2 lags)	0.061	0.339***	0.118	0.162**	0.039	0.128*	0.129	0.298***	0.217***
	(0.086)	(0.067)	(0.084)	(0.069)	(0.080)	(0.072)	(0.081)	(0.074)	(0.080)
CCI (3 lags)	0.127*	0.072	0.051	0.176***	0.178***	0.156**	0.128**	-0.041	0.068
	(0.070)	(0.060)	(0.065)	(0.066)	(0.062)	(0.068)	(0.059)	(0.069)	(0.074)
Adj R^2	0.928	0.840	0.938	0.861	0.841	0.808	0.887	0.924	0.877
AIC	1477.342	1587.73	1476.808	1615.516	1547.046	1682.798	1475.798	1492.514	1636.815
BIC	1504.344	1614.732	1503.81	1642.519	1574.049	1709.8	1502.8	1519.516	1663.817

Note: Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

5. Discussion

The most prominent result of this thesis is the fact that Donald Trump's Twitter has a small effect on consumer confidence, across most specifications. Indicating that there exists a positive relationship. The extent of this effect is shown to be relatively constant across the different models, only observing smaller variations in coefficients.

According to these findings, President Trump is able to boost consumer confidence through changing the sentiment in his tweets, hence influence the public's perception of current and future economic conditions. Through highlighting and repeating positive changes in economic fundamentals, he is able to exaggerate economic conditions, relative to economic reality. In similar ways to how news media sentiment is able to enhance the public's reaction to economic changes, we find evidence suggesting that President Trump's Twitter has comparable influential ability. Another interesting link is the predictive power of CCI on future consumption, which is intuitively reasonable and has been proven in multiple studies. Previous literature has found that when news media is exaggerating economic conditions, it can cause increased spending and employment (Starr, 2012). Extending this link to Donald Trump's Twitter sentiment raises the question whether his sentiment potentially can boost economic activity and influence future consumption.

Nevertheless, President Trump has created a valuable tool through his Twitter account, using his presidential authority combined with the reach of social media. The consumer confidence index reached an 18-year high in February 2018 and is still upholding higher ratings compared to the last decade. Based on these ratings, President Trump has been doing a remarkable job in hyping the economy and cheering for the nation. He has become a national cheerleader with the American people as his team. Regardless of how the team is doing, his job of strengthening and motivating them is remarkable. He understands what the team needs to hear and uses a modern, digital tool to continuously remind them that things are getting better. One might blame his presidency on other contributing factors, such as growing ignorance and anti-intellectualism, but nonetheless, his presidency has created optimism among the public. He has managed to spread his positive messages through Twitter to such an extent that it is affecting consumers perception of current and future economic conditions. Whether this is a strategic, calculated plan or simply a coincidence is irrelevant. He is a man of his time and undoubtedly The Cheerleader of The United States.

6. Concluding remarks

In this thesis, we examined whether the president of U.S. Donald Trump can affect the public's perception of current and future economic conditions, through his Twitter account. We conducted two separate sentiment analyses of news media and his Twitter, followed by a study of their effect on consumer confidence on a regional and national level. Our findings suggest that president Trump is able to affect consumer confidence, as an extension to traditional news media. Previous literature has argued that news media is able to enhance the effect on the public's perception of changes in macroeconomic indicators, as does Donald Trump through his Twitter. Using repetition and truncated language as rhetorical tools, Trump continuously highlights changes in economic fundamentals, portraying the economy in a further optimistic light. Moreover, conducting a similar analysis for nine regions within the U.S. we found that Trump has a stronger influence in regions that are regarded as Republican given the latest election results. We attribute this result to the fact that the constituents of these regions are stronger supporters of the political ideas and agenda deployed by Donald Trump.

Our contribution to the existing literature is the investigation of Twitter as an extension of news media, in the context of delivering economic news to the public. Unlike the previous literature that focuses on the sentiment in either news media or social media, our primary focus is the sentiment in a single Twitter account, in combination with news media, and how it can affect the consumer confidence index.

6.1 Future Research

The use of Twitter among politicians is increasing, which makes this type of study even more relevant for the future. Considering Twitter's role in the outcome of the 45th presidential election in the United States, the value of social media as a political tool will no longer be underestimated. It would be interesting to replicate our study on Trump in a future period, in order to collect more observations and improving the relevancy of the selected sample period even further. Furthermore, as other individuals with power have realized the potential impact this social media has, it might be relevant to study their Twitter and its impact on for example CCI.

Another interesting study would be to allow for asymmetric reactions from Trump's tweets. This field has been developed with a focus on CCI, media and economic fundamentals. However, extending this field with the inclusion of Trump's Twitter and asymmetric reactions could potentially constitute an interesting and current research topic.

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Appendices

Appendix I

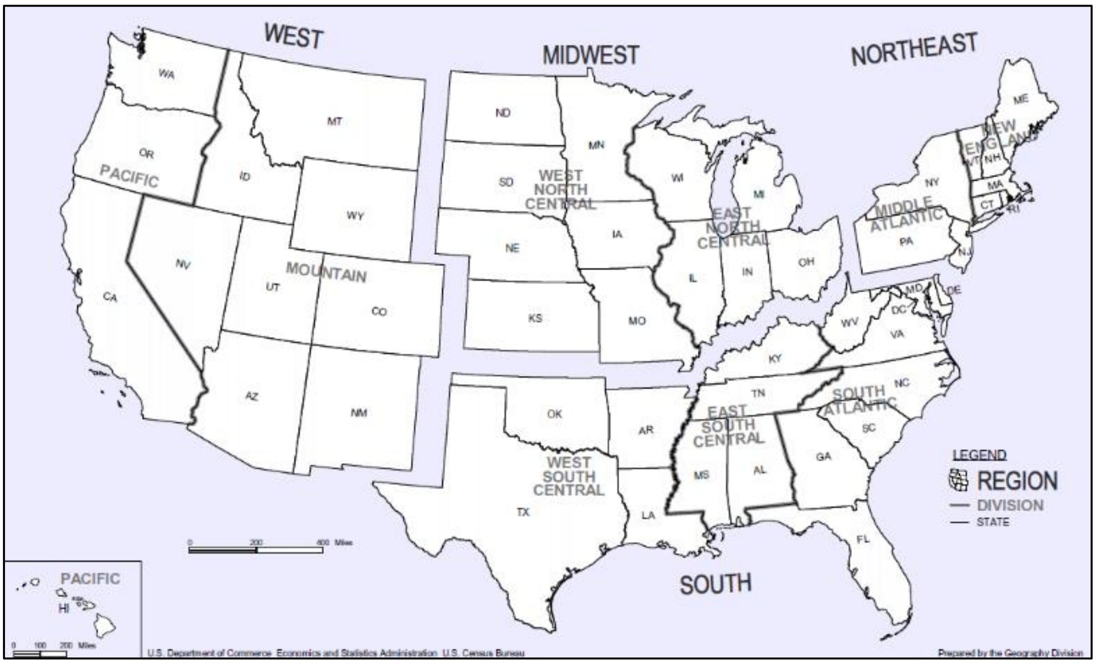
We used the Consumer Confidence Indexes for nine pre-defined regions, so-called Census regions (Census Bureau, 2015). In categorizing them as either Republican (R) or Democrat (D), we use the electoral voting results from the 2016 Presidential election (Politico, 2016). Adding all the electoral votes from each state and then connecting it to their Census division, we can thus calculate the percentage of Republican electoral.

Table A.1 Electoral votes for each respective Census region.

Region	Electorals (R)	Electoral (D)	% (R)[i]	Conclusion
East North Central	55	20	73%	Republican
West North Central	33	10	77%	Republican
South Atlantic	74	29	72%	Republican
East South Central	24	0	100%	Republican
West South Central	59	0	100%	Republican
New England	0	32	0%	Democrat
Middle Atlantic	20	43	32%	Democrat
Pacific	3	78	4%	Democrat
Mountain	16	20	44%	Neutral

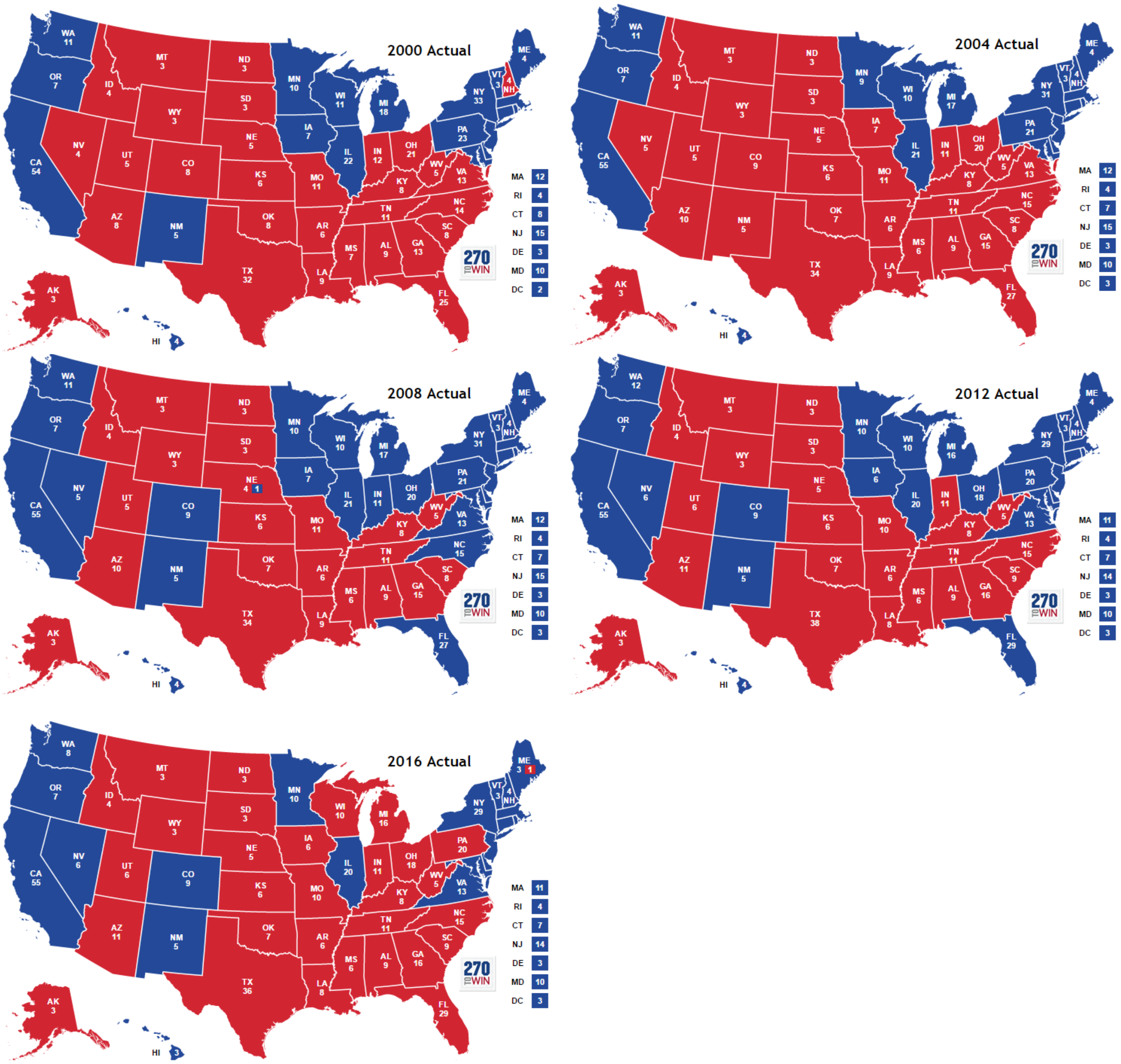
[i] This column describes the fraction of total Republican electoral votes

Figure A.1 Census Regions and Divisions of the United States.



Source: Census Bureau (2015). Regions and Divisions of the United States [pdf], Available online: https://www2.census.gov/geo/pdfs/maps-data/maps/reference/us_regdiv.pdf, [Accessed 12 March 2018]

Figure A.2 Historic overview of all election results in the United States, in terms of electorals, since 2000.[7]



[7] This figure is a combination of 5 web-pages from one source:
270 To Win (n.d.). 2000 Presidential Election, Available Online: https://www.270towin.com/2000_Election, [Accessed 17 May 2018]
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Appendix II

Table A.2 Illustrates the regression results including the control variables (C*x*) for the general model.

	C1	C2	C3	C4	C5
TRUMP	23.540***	17.633***	17.350***	11.645	12.206
	(5.537)	(5.297)	(5.529)	(13.877)	(14.206)
TRUMP (1 lag)				6.235	5.113
				(15.936)	(15.912)
NEWS	0.468***	0.386***	0.378***	0.275**	0.283**
	(0.118)	(0.115)	(0.118)	(0.126)	(0.127)
NEWS (1 lag)				0.226**	0.199*
				(0.107)	(0.109)
CCI (1 lag)	0.511***	0.318***	0.314***	0.294***	0.294***
	(0.057)	(0.069)	(0.072)	(0.070)	(0.074)
CCI (2 lags)		0.149**	0.155**	0.135**	0.143**
		(0.065)	(0.066)	(0.063)	(0.065)
CCI (3 lags)		0.168**	0.167**	0.171**	0.171**
		(0.067)	(0.066)	(0.066)	(0.066)
%Δ UR (1 lag)	-47.495	-38.044	-26.197	-37.495	-26.531
	(38.015)	(35.288)	(33.579)	(34.881)	(33.821)
%Δ UR (2 lags)			21.238		24.178
			(30.244)		(29.973)
%Δ UR (3 lags)			-41.787		-36.778
			(30.057)		(29.889)
%Δ CPI (1 lags)	-639.976**	-758.145***	-673.689**	-834.895***	-756.755**
	(288.530)	(268.958)	(299.155)	(275.877)	(312.482)
%Δ CPI (2 lags)			-215.793		-180.034
			(287.444)		(291.572)
%Δ CPI (3 lags)			489.021*		441.424
			(284.160)		(281.370)
%Δ FED	15.241**	17.172***	18.402***	14.902***	16.380***
	(5.883)	(5.436)	(5.673)	(5.295)	(5.590)
%Δ FED (1 lag)	11.225*	12.686*	11.543*	13.169**	12.128*
	(6.560)	(6.521)	(6.901)	(6.259)	(6.683)
%Δ DJIA	3.809	3.363	3.808	6.963	7.063
	(20.517)	(19.820)	(19.815)	(19.529)	(19.760)
%Δ GAS	-26.873*	-26.845**	-25.359*	-25.011**	-23.682*
	(13.899)	(12.249)	(13.136)	(12.218)	(13.176)
Adj R^2	0.813	0.826	0.824	0.828	0.825
AIC	1691.603	1666.915	1662.5	1666.641	1663.237
BIC	1732.161	1714.168	1723.171	1720.646	1730.65

Note: Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table A.3 Additional results obtained in the regional analysis.

	East North Central (R)	West North Central (R)	South Atlantic (R)	East South Central (R)	West South Central (R)	New England (D)	Mid Atlantic (D)	Pacific (D)	Mountain (N)
TRUMP	10.734**	7.462	11.940*	22.584***	7.424	8.865**	8.595**	4.950	8.475
	(3.376)	(4.518)	(3.996)	(6.275)	(4.665)	(3.933)	(3.704)	(3.339)	(5.464)
NEWS	0.236***	0.364***	0.344***	0.421***	0.303***	0.437***	0.325***	0.371***	0.540***
	(0.064)	(0.079)	(0.075)	(0.089)	(0.067)	(0.100)	(0.062)	(0.071)	(0.097)
CCI (1 lag)	0.704***	0.398***	0.681***	0.414***	0.597***	0.459***	0.546***	0.561***	0.473***
	(0.060)	(0.066)	(0.069)	(0.065)	(0.078)	(0.067)	(0.074)	(0.069)	(0.061)
CCI (2 lags)	0.160**	0.371***	0.155**	0.245***	0.156**	0.208***	0.206***	0.271***	0.258***
	(0.063)	(0.065)	(0.068)	(0.060)	(0.065)	(0.065)	(0.066)	(0.063)	(0.062)
Adj R^2	0.929	0.843	0.939	0.859	0.838	0.806	0.888	0.926	0.877
AIC	1485.56	1593.95	1481.24	1627.34	1558.49	1693.66	1483.74	1496.78	1643.73
BIC	1509.22	1617.61	1504.90	1651.00	1582.14	1717.32	1507.40	1520.43	1667.39

Note: Robust standard errors in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Table A.4 Illustrates regression results for the Census regions that are regarded as Republican.

	East North Central (R)		West North Central (R)		South Atlantic (R)		East South Central (R)		West South Central (R)	
	C1	C2	C1	C2	C1	C2	C1	C2	C1	C2
TRUMP	10.818**	14.350*	10.850*	9080	11.721**	13.993***	22.105***	23.761***	7.502	4.371
	(3.167)	(8.233)	(4.605)	(8.855)	(3.792)	(3.670)	(5.983)	(8.976)	(4.391)	(6.348)
Trump (1 lag)		-8.329		18.172**		-1.518		-1.133		2.564
		(8.515)		(8.458)		(4.549)		(8.382)		(6.662)
NEWS	0.217***	0.141*	0.313***	0.199**	0.320***	0.269***	0.339***	0.152	0.223***	0.113
	(0.062)	(0.072)	(0.084)	(0.091)	(0.071)	(0.077)	(0.087)	(0.096)	(0.074)	(0.091)
NEWS (1 lag)		0.153*		0.309***		0.125		0.424***		0.262***
		(0.085)		(0.102)		(0.079)		(0.102)		(0.086)
CCI (1 lag)	0.651***	0.634***	0.295***	0.233***	0.612***	0.588***	0.287***	0.244***	0.510***	0.481***
	(0.069)	(0.071)	(0.075)	(0.077)	(0.070)	(0.069)	(0.057)	(0.060)	(0.079)	(0.080)
CCI (2 lags)	0.063	0.067	0.358***	0.328***	0.130	0.127	0.167**	0.132*	0.083	0.072
	(0.086)	(0.087)	(0.067)	(0.066)	(0.083)	(0.084)	(0.067)	(0.070)	(0.079)	(0.080)
CCI (3 lags)	0.136**	0.136**	0.090	0.106*	0.067	0.073	0.214***	0.215***	0.187***	0.172***
	(0.066)	(0.069)	(0.058)	(0.060)	(0.063)	(0.064)	(0.066)	(0.063)	(0.062)	(0.066)
%Δ UR (1 lag)	-17.735	-10.552	-43.991*	-50.509**	-15.172	-12.737	-42.290	-32.216	-11.181	-6.890
	(19.461)	(19.654)	(25.467)	(23.935)	(20.716)	(21.001)	(27.318)	(24.671)	(22.542)	(22.571)
%Δ CPI (1 lag)	-176.077	-215.496	-394.871*	-526.191**	-610.010***	-649.038***	-643.161***	-775.956***	-378.151**	-452.111**
	(198.742)	(215.048)	(213.429)	(233.468)	(171.404)	(174.584)	(247.049)	(250.401)	(183.121)	(186.383)
%Δ FED	1.014	-0.593	7.407	4.449	9.552**	8.360*	11.629**	6.730	14.553***	11.393**
	(3.807)	(3.771)	(4.867)	(4.752)	(4.605)	(4.655)	(4.716)	(4.485)	(5.309)	(5.070)
%Δ FED (1 lag)	8.929**	9.525**	9.673**	10.074**	6.111*	6.691**	11.338**	12.639***	3.725	4.123
	(4.087)	(3.883)	(4.686)	(4.470)	(3.376)	(3.342)	(4.985)	(4.656)	(4.067)	(3.911)
%Δ DJIA	9.889	12.470	17.627	19.527	6.319	7.434	10.513	14.263	11.433	13.104
	(12.027)	(11.907)	(13.836)	(13.799)	(14.171)	(14.108)	(16.706)	(16.121)	(15.288)	(15.036)
%Δ GAS	-17.783**	-17.014*	-21.386**	-18.332**	-3.167	-2.271	-16.964	-14.402	-14.700	-13.109
	(8.969)	(8.807)	(8.968)	(8.886)	(8.122)	(8.320)	(12.383)	(12.069)	(10.679)	(10.385)
Adj R^2	0.931	0.932	0.850	0.858	0.942	0.942	0.872	0.882	0.850	0.855
AIC	1474.622	1472.916	1579.33	1569.923	1467.489	1468.574	1603.03	1587.958	1540.21	1534.728
BIC	1521.876	1526.921	1626.584	1623.927	1514.743	1522.578	1650.284	1641.963	1587.464	1588.732

Note: Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.4 *(Continued)*

	New England (D)		Mid Atlantic (D)		Pacific (D)		Mountain (N)	
	C1	C2	C1	C2	C1	C2	C1	C2
TRUMP	7.192**	6.469	6.547**	5.925	6.663**	3.624	7.748*	1.425
	(5.474)	(4.962)	(3.803)	(5.027)	(3.342)	(4.959)	(5.257)	(8.741)
Trump (1 lag)		7.016		4.150		2.964		8.381
		(4.042)		(5.392)		(5.489)		(10.780)
NEWS	0.360***	0.236*	0.308***	0.233***	0.359***	0.312***	0.513***	0.400***
	(0.115)	(0.126)	(0.063)	(0.073)	(0.071)	(0.074)	(0.103)	(0.118)
NEWS (1 lag)		0.252**		0.177**		0.136*		0.293**
		(0.107)		(0.078)		(0.074)		(0.120)
CCI (1 lag)	0.335***	0.310***	0.453***	0.411***	0.486***	0.454***	0.406***	0.365***
	(0.068)	(0.069)	(0.072)	(0.073)	(0.064)	(0.068)	(0.068)	(0.070)
CCI (2 lags)	0.142**	0.126**	0.136*	0.138*	0.335***	0.322***	0.235***	0.207**
	(0.065)	(0.063)	(0.077)	(0.077)	(0.070)	(0.071)	(0.080)	(0.083)
CCI (3 lags)	0.177***	0.180***	0.136**	0.133**	-0.040	-0.023	0.078	0.088
	(0.067)	(0.066)	(0.059)	(0.060)	(0.065)	(0.068)	(0.073)	(0.073)
%Δ UR (1 lag)	-31.952	-30.720	-29.932	-29.258	-60.888***	-60.731***	-21.737	-21.939
	(35.413)	(34.805)	(19.339)	(20.146)	(19.975)	(20.692)	(28.547)	(30.024)
%Δ CPI (1 lag)	-762.726***	-850.493***	-408.264*	-484.117**	-420.302**	-467.675***	-326.266	-417.368
	(270.467)	(276.496)	(207.988)	(213.997)	(167.948)	(166.974)	(265.777)	(274.414)
%Δ FED	16.250***	13.646**	8.951**	7.155*	10.680***	9.271***	12.755**	9.444
	(5.621)	(5.476)	(3.691)	(3.710)	(3.365)	(3.410)	(5.515)	(5.967)
%Δ FED (1 lag)	13.147**	13.717**	5.314*	5.886*	5.961	6.509*	4.828	5.468
	(6.514)	(6.208)	(3.213)	(3.178)	(3.752)	(3.800)	(4.662)	(4.749)
%Δ DJIA	0.646	4.145	-2.329	-0.359	-9.134	-7.770	-12.183	-10.312
	(20.441)	(20.059)	(13.087)	(13.138)	(13.130)	(13.066)	(18.523)	(18.401)
%Δ GAS	-24.368*	-22.069*	-15.672**	-13.938*	-9.579	-8.525	-9.238	-7.603
	(12.434)	(12.406)	(7.515)	(7.594)	(7.256)	(7.259)	(11.751)	(12.072)
Adj R^2	0.824	0.826	0.894	0.896	0.932	0.933	0.879	0.882
AIC	1669.308	1668.075	1467.029	1464.906	1474.188	1475.007	1637.849	1634.372
BIC	1716.562	1722.079	1514.283	1518.911	1521.442	1529.012	1685.103	1688.377

Note: Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1