Reading Between the (Party) Lines:
How Political News is Seen and Shared

by

Sophie Beiying Chou

Submitted to the Program in Media Arts and Sciences,
School of Architecture and Planning
in partial fulfillment of the requirements for the degree of

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Abstract

This thesis uses mixed methods and datasets to explore how political news is perceived and shared within and across party lines in the context of the 2016 US presidential elections. We begin by examining the impact of political context versus article content on the reader through a crowdsourced study, and follow up with a large scale analysis of story sharing on the social platform Twitter to find cases where popularity transcends political affiliation.

In Part One, we look at reader *reactions*. We investigate the question of trust in political news by analyzing the impact of content features (reading level of the article) versus context clues (media brands). We find that reading level has no significant impact on whether or not political news is seen as trustworthy, and that media brand, as well as candidate loyalty, matters above all other aspects in biasing the reader. This assertion holds when *the content itself remains constant*, and the same news story is shown as attributed to different media outlets, resulting in different levels of trust.

In the second part of this thesis, we focus on reader *actions*. In particular, we look at how political news stories from the same time period are shared on the social media platform Twitter. As we found candidate loyalty and media brand perceptions to be significant influences on the reader's opinion of news, we are particularly interested in examining features that cause stories to become popular beyond political boundaries. Extending previous studies relating different emotional responses and virality, we look for text that might trigger an emotional response in the reader. We find that the degree of emotionality in a story as well as the direction of sentiment transcends affiliation and degree of political engagement in sharing behavior.

Together, these two parts hope to form a more complete view of factors affecting and driving readers in an election cycle that is heavily influenced by media coverage, both traditional and new.

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Chapter 1

Introduction

Does anyone trust the news anymore? Not according to the latest Gallup Poll, which showed that only 4 in 10 Americans believe that mass media does a good job of reporting the news "fully, fairly, and accurately." It's a major decline since the poll was first taken in 1999, back when more than half (55%) of Americans believed the news was trustworthy [30].

And the trend has been steadily downward: in short, the majority of Americans have had little to no trust in mass media news coverage since 2007: a discouraging view for a tumultuous time in journalism.

But beyond frustrated readers and reporters, why does distrust in the news matter? For one, media bias—or at the very least, the *belief of* a biased media bias—may have a significant impact on the practice of democracy. A 2006 study from Georgetown University shows that those with more negative attitudes towards the news tend to be more highly influenced by their partisan prior beliefs and less by contemporary issues and messages when voting [21]. This implies that distrust of media plays a large role in the polarization of American politics.

Additionally, our reactions to news stories– as well as politics at large– are largely driven by emotion. Historical trends, as well as present-day models, show a process largely influenced by feelings rather than facts.

In light of the upcoming 2016 elections, Part I explores perceptions of media trust in coverage of the presidential candidates. Claims of media bias and favoritism are especially high-stakes in election years, where trust has been shown to plummet [30].

We begin by examining some of the factors that contribute to the perception of media bias. In particular, how does the *content* of a story (reading level and vocabulary) affect the reader versus the *context* (source)? Although studies have been conducted to both examine the psychological effect of wording on believability and the impact of media brands and bias, separating and comparing these two factors remains largely unexamined [40, 8]

To test our hypotheses on news trust, we perform a study on the crowdsourcing platform CrowdFlower. We manipulate the source of the story to examine effects of media brands on the reader, and also compare fairness and trust rankings between high and low reading level stories.

Although the general consensus of mistrust is clear, perception of media bias is a complex phenomenon to dissect, as it combines social and psychological effects with the traits of the story itself. This section hopes to shed light on the interplay between some of those factors.

Chapter 2

In Media We ... Trust?

Despite the news media ecosystem's rapid evolution in the past decade, the question of fairness in reporting remains a valued one. Although counterarguments for subjective reporting exist (Glenn Greenwald, most famous for his coverage of whistleblower Edward Snowden's leaks, said that "All journalism is a form of activism. Every journalistic choice necessarily embraces highly subjective assumptions–cultural, political or nationalistic–and serves the interests of one faction or another"), fair treatment of subjects and sources remain a central tenant to most publications [2].

But an attempt at fairness on the side the reporter is not always perceived in equal effect under the eyes of the reader. Presenting contradictory facts to a reader's beliefs can even sometimes *strengthen* their oppositions to it, a concept known as "motivated skepticism" [35].

In this section, we examine the impact of distrust in media, and explore the theories behind three main potential sources of media distrust: the characteristics of the reader, the source of the story and its use of language.

2.1 Why Does Media Trust Matter?

The idea that mass media has a large influence on the ramifications of democracy is nothing new. In 1922, political commentator, reporter, and writer Walter Lippman wrote about its central role in shaping public opinion:

> Each of us lives and works on a small part of the earth's surface, moves in a small circle, and of these acquaintances knows only a few intimately. Of any public event that has wide effects we see at best only a phase and an aspect. This is as true of the eminent insiders who draft treaties, make laws, and issue orders, as it is of those who have treaties framed for them, laws promulgated to them, orders given at them. Inevitably our opinions cover a bigger space, a longer reach of time, a greater number of things, than we can directly observe. They have, therefore, to be pieced together out of what others have reported and what we can imagine. Yet even the eyewitness does not bring back a naive picture of the scene. [24]

Many of the worries that Lippman had about the effects of poorly disseminated truth have been later confirmed in experimental studies. In short, when faced with a large and mistrusted news environment, we tend to rely on *confirmation bias* when searching for information. This term, first coined in 1988, describes the psychological phenomeon of seeking or analyzing new information in ways that align with one's existing beliefs, expectations or prior hypotheses [27].

Using a Bayesian voting model, a study from Georgetown University in 2005 was able to show that voters with low trust and a high dislike for the news media are significantly more influenced by their existing party identifications in casting ballots than current economic factors [21]. The study attributes increasing polarization in the American political sphere with increasing lack of trust in the news, a serious implication for the highly polarized 2016 presidential elections. Moreover, distrust of media implies a large information loss in the public, whose avoidance of diverse ideas means a narrowing of information flow [20].

2.2 How is Media Trust Formed?

2.2.1 The Role of the Reader

The perception of media bias is a cornerstone component of distrust in the news. After all, most Americans claim that they want to read news that's unbiased. A survey from Pew Research in 2012 showed that more than two-thirds (68%) of readers want to read political articles with a neutral stance, compared to just a little less than a quarter (23%) of those who want to read those stories that share their point of view [4]. But what exactly does that entail?

It comes as no surprise that our own political stances have a significant effect in our perceptions of bias in the media. On whole, conservative readers tend to view media as more biased than both Democrats and Independents (49% to 32% and 35%, respectively)[4]. Partisans have also been shown to view the news as antagonistic to their beliefs, a phenomenon known as the "hostile media effect".

The effect, first studied in the 1980s, showed that when faced with the same piece of news media about the Sabra and Shatila massacre in Beirut, pro-Israeli and pro-Palestinian students both claimed the news clip was biased in favor of the other side [37]. It has since been repeated in a variety of contexts to the same effect.

What the story is reporting does not matter so much as the individual's attitude *towards* that issue. In 1988, Albert Gunther found a curvlinear effect between the viewer's polarization towards an issue and their trust in the media to fairly cover it [18]. In doing so, he suggests two models of persuasion to help understand media processing: first, the cognitive response theory, which predicts more portential for attitude change when the reader is highly involved in the content, as they are processing information more deeply [10]. Social judgement theory, on the other hand, expects less change in attitude when the reader is highly involved or polarized about a subject, as they will simply reject the new information [32]. These two opposing theories help explain the presence of a curvlinear relationship to exposure to news media and resulting media trust.

2.2.2 The Role of Media Brands

The media, of course, is not just one unified mass, and in an increasingly fragmented ecosystem, the role of brands is a crucial factor in media trust. With the rise of the internet, the past decade has seen an explosion of new media platforms and publications, as well as significant transformations in style and audience in existing outlets.

Although the studies above present the media as one unified mass, there is a significant amplifying effect of hostility and bias perception depending on the reader's prior connotations of a news outlet. In 2008, researchers Matthew Baum and Phil Gussin showed significant differences in the evaluation of a piece of news content depending on whether it was labeled to be from CNN, Fox, or a fictional news outlet [8]. They concluded that media bias is very much "in the eye of the beholder," as viewers make information shortcuts dependent on media brand to jump to conclusions beyond their own partisanship and the content of the story.

2.2.3 The Role of Language

Finally, the role of language–in media as well as politics–cannot be overlooked. A recent article in the Boston Globe analyzed the language of presidential candidate Donald Trump to be at a fourth grade level– and more successfully appealing to voters [39]. (Those who have been speaking at lower grade levels in the 2016 election cycle have also been winning more votes.)

Analysis by media outlet Vocativ showed a negative correlation between presidential speech level over time [15].

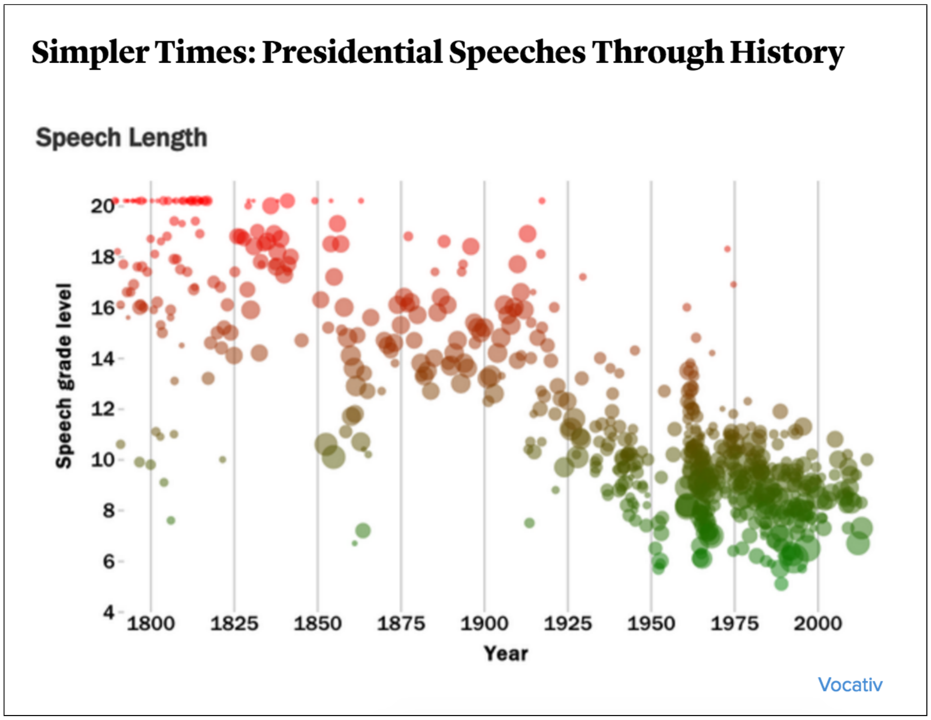

Figure 2-1: Language of Presidential Speech Decline

Yet political news *coverage* occupies a different space of language and purpose, often with the intent of reporting statistics and facts in a scientific nature using a specified technical vocabulary. And when the reader processes information of a scientific nature, a funny effect has been shown: that more complex language, with more technical jargon and sophisticated construction, might actually *increase* appeal and the likelihood of trust. In 2008, Weisberg et. al showed that the addition of "neuroscience" significantly increased the likelihood of believability in explaining how the brain works, versus the same explanation in simple, everyday language [40]. These two factors are both at play when considering the impact of the language in political news and its perceived truthworthiness, for the articles are often *both* a reflection of a political candidate as well as its analysis of her or him.

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Chapter 3

Tools for Dissecting Trust

3.1 Computing Reading Level

3.1.1 Flesch-Kincaid Readability Tests

In this study, we focus primarily on the Flesch-Kincaid (F-K) tests for estimating text readability. Originally developed for the U.S. Navy in 1975 for assessing the difficulty of technical manuals, the F-K reading level corresponds roughly to U.S. grade level and the reading ease score is inversely proportional to the grade level on a scale from 0 to approximately 120 [19].

We chose the F-K tests over other comparable ones due to its popularity in educational assessment and other applications, including in legislation. For example, it is required by law in Florida that life insurance policies have a Flesch reading ease of 45 or greater (less than 12th grade in reading level) [23]. The F-K tests are also bundled in many common word processing services, including Microsoft Office Word. As a comparison, basic article analysis is also computed using the Gunning fog index (see Section 5.2.1).

The formula for Flesch reading ease is as follows:

$$206.835 - 1.015\left(\frac{\text{total words}}{\text{total sentences}}\right) - 84.6\left(\frac{\text{total syllables}}{\text{total words}}\right)$$

And for reading grade level:

$$0.39\left(\frac{\text{total words}}{\text{total sentences}}\right) + 11.8\left(\frac{\text{total syllables}}{\text{total words}}\right) - 15.59$$

The two formulas are not directly comparable due to the difference in weighting factors. For ease of metaphor, we use the grade level tests in our analysis. Syllable length is highly weighted in this formula, so it is possible to generate a story of very high reading level that consists of a single word in a single sentence (the longest English word, *pneumonoultramicroscopicsilicovolcanoconiosi*, a type of lung disease, has a reading grade level of 197.2), which is a limitation of the method, since texts with polysyllabic words are not always necessarily more difficult to read.

3.1.2 Comparison to Other Reading Tests

3.2 Crowdsourcing Science

Along with an explosion of media outlets and new media platforms, the rise of the internet has also introduced alternative methods to traditional ways of conducting behaviorial studies. In this thesis, we focus on crowdsourcing as our primary method of collecting data.

In addition to low cost, we chose crowdsourcing due to its: A) democratizing effect in research and B) subject pool diversity. Crowdsourcing has the benefit of creating a lower barrier for experimentation and replication, allowing researchers to have access to subject pools they would not have otherwise in equal opportunity [25]. Moreover, as our study involves political attitudes, using a crowdsourcing platform allows us to collect geographically diverse data that is more representative than if it were performed locally.

3.2.1 CrowdFlower

We perform the following studies on the platform CrowdFlower, a popular crowdsourcing platform and marketplace. We chose this platform due to its focus on higher quality data over volume and the ability to filter contributors by level of skill [5]. Results have been found comparable to those on Amazon Mechanical Turk (the most commonly used platform) in prior studies of annotation tasks [14].

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Chapter 4

Study

4.1 Motivations

This study sets out to tackle the question of reading level's effect in perceptions of news bias. In particular, how does it compare to factors associated with latent biases of the reader, such as media brand?

Although the body of literature in Chapter 2 examines the theories behind partisanship and media branding, little work has been done to compare those contextual effects with the effects of *content* within a story, such as language use.

This thesis tests five hypothesis.

We explore two novel hypotheses testing reading level effects:

- **H1**: High reading level stories increase trust in the story.
- **H2**: However, they decrease perceptions of fairness.

As well as two comparing the role of *content* versus *context*:

- **H3**: Media brand has a stronger role in determining story trust than reading level.

- **H4**: Media brand has a stronger role in determining story fairness than reading level.

And verifying former theories, we expect that:

- **H5**: Stories shown to be from outlets of aligned political party score significantly higher on both trust and fairness than those of the opposite.

We hypothesis **H1**: that high reading level of stories increase trust based off the work from Weisberg et. al showing that neuroscience explanations sway believability of scientific explanations, due to the field-specific nature of political reporting [40].

Conversely, we predict **H2** that it creates a decrease in the perception of fairness in the story, due to the polarizing nature of political news and the fact that more complex stories could cause a partisan individual to more quickly reject what appears as an onslaught of conflicting information [10].

We hypothesize **H3** and **H4** that media brand effects outweigh content in determining both trust and fairness.

Finally, we expect to see hostile media effects (**H5**) to emerge.

4.2 Experimental Design

Our experiment has a 4 x 2 mixed-factorial design.

	Source: None	**Source: AP**	**Source: Fox**	**Source: CNN**
High Reading Level	Clinton, Cruz, Sanders, Trump	Clinton, Cruz, Sanders, Trump	Clinton, Cruz, Sanders, Trump	Clinton, Cruz, Sanders, Trump
Low Reading Level	Clinton, Cruz, Sanders, Trump	Clinton, Cruz, Sanders, Trump	Clinton, Cruz, Sanders, Trump	Clinton, Cruz, Sanders, Trump

Table 4.1: Main Study Design

In this study, reading level of articles and candidates featured in the articles were treated as within-subject variables, and the source of the story between-subjects.

Each participant reads eight stories, two each of high and low reading level per candidate. However, to examine effects of media brands and reader bias, we manipulate the source attributed to the story, building off Baum's research in media brands and television reporting [8].

All eight stories in this study were in fact written by the Associated Press, however, readers are divided into four groups receiving different labels. In group A, readers were shown the headline and text of the story with no other context. In group B, readers were additionally shown that the story was from the Associated Press (true label). In groups C and D, readers were shown that the story was from CNN and Fox News, respectively.

This setup was created to eliminate some of the confounding effects from using stories from different sources (writing style, focus of content, slant, etc.), while directly observing the effect of revealing a specific source to the reader. The Associated Press was chosen as the source of the stories as it is the highest circulation newswire service in the United States, and has 14,000 members that use its content [29]. Notably, both CNN and Fox News publish content in full or part from the Associated Press, although the specific stories chosen had not been published in full by either to avoid bias.

After each article, we ask the reader to rank the fairness of the story on a 5-point

Likert scale as well as its truthworthiness.

4.2.1 Dataset

Eight stories were chosen for this study: two (high and low reading level) for four presidential candidates. All eight stories were written by reporters from the Associated Press (although they may have been republished elsewhere).

To form the initial pool of articles, we programatically collected stories from the RSS feeds of the Associated Press online every hour over a 3-month period: from January 1, 2016 of the election year to March 1, 2016 (Super Tuesday). Based on the results of Super Tuesday, we then selected four candidates for this study by delegate count: Hillary Clinton (1,279), Bernie Sanders (1,027), Donald Trump (743), and Ted Cruz (517) [6].

News articles were then separated into single-candidate stories (i.e. articles featuring primarily one candidate in the headline) to be able to measure more clearly the perceived bias per candidate. This was done programatically using regular expressions to determine if a headline contained one candidate and one candidate only. A dictionary of related names was created to make sure that stories were correctly categorized (i.e. "Hillary", "Clinton", and "Hillary Clinton" were to be categorized as pertaining to "Hillary Clinton" but not if preceded by "Bill").

Reading level cutoffs were then made by taking the bottom and top 25% percentile of Flesch-Kincaid scores for each candidate. From the set of stories that made the cutoff, we formed pairs of high and low reading level stories from each topic. The topic with the highest distance between reading level in the pair was chosen for each candidate.

4.2.2 Survey Design

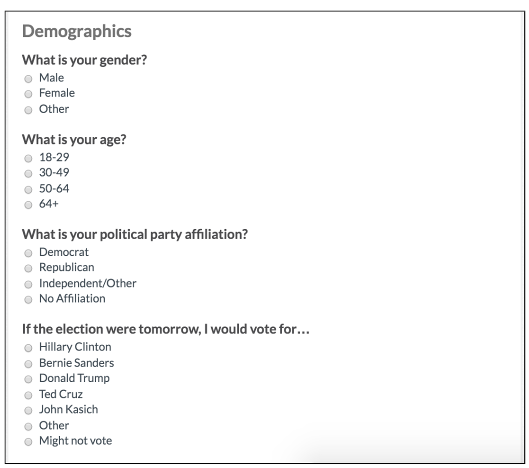
We designed four surveys (1 per group) on the platform CrowdFlower. Each participant was randomnly assigned to a group and could not take the survey more than once. The eight stories were shown (in a randomized order), and each story was followed up by two scoring questions pertaining to fairness and trustworthiness.


I find this article fair.
- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

I find this article trustworthy.
- Strongly Agree
- Agree
- Neutral
- Disagree
- Strongly Disagree

Figure 4-1: Scoring Questions for Survey

The survey concluded with an abbreviated standard demographic survey as well as a political affiliation survey adapted from Pew's standard polling survey [3]. These more personal questions were placed at the end to prevent priming readers beforehand.


Demographics

What is your gender?
- Male
- Female
- Other

What is your age?
- 18-29
- 30-49
- 50-64
- 64+

What is your political party affiliation?
- Democrat
- Republican
- Independent/Other
- No Affiliation

If the election were tomorrow, I would vote for…
- Hillary Clinton
- Bernie Sanders
- Donald Trump
- Ted Cruz
- John Kasich
- Other
- Might not vote

Figure 4-2: Demographic Questions for Survey

Finally, we asked readers to report whether or not they migh have read the stories before.

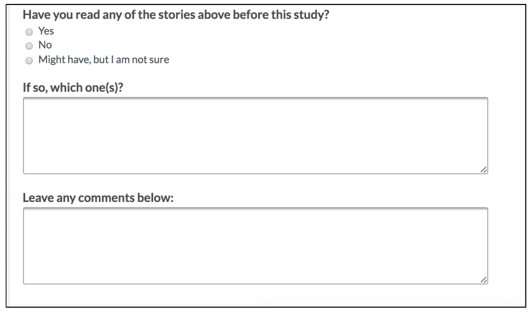


Figure 4-3: Comments for Survey

We ran the survey of a duration of hours and had 40 participants sign up per group, for a total of 160 participants.

4.2.3 Quality Control

CrowdFlower has a built-in "Test Question" feature that allows for the rejection of a annotator whose answers to specific questions do not lie within a threshold (default 70%) of the "correct" answer or whose answers lay outside the standard variation compared to others.

However, since the questions we asked were by nature subjective and therefore outliers and disagreements in answers could imply signal rather than noise, we chose to monitor for quality using other metrics instead. CrowdFlower was not designed explicitly for survey-like tasks, and therefore there were no options for different screening methods or questions. Gold Questions on the platform are selected by the creator within the set of all questions being recorded.

Because of this, we monitored quality of results in two ways:

First, by setting a minimum of time of 360 seconds to complete the task of reading 5 stories for a task to be accepted.

Second, by selecting only Level 3 contributors on CrowdFlower as suggested on their website for handling survey-like tasks [1].

Level 3 contributors are described as those who "have completed over a hundred Test Questions across hundreds of different Job types, and have a near perfect overall Accuracy" [5]. This is the highest category of contributor.

Users were also only allowed to answer the set of questions once.

$0.80 was given per survey, as suggested by MIT Committee on the Use of Humans as Experimental Subjects. The average response time per survey was 09:20 min.

4.3 Survey Results

In this section, we report descriptive analyses on the nature of the data collected.

4.3.1 Demographics

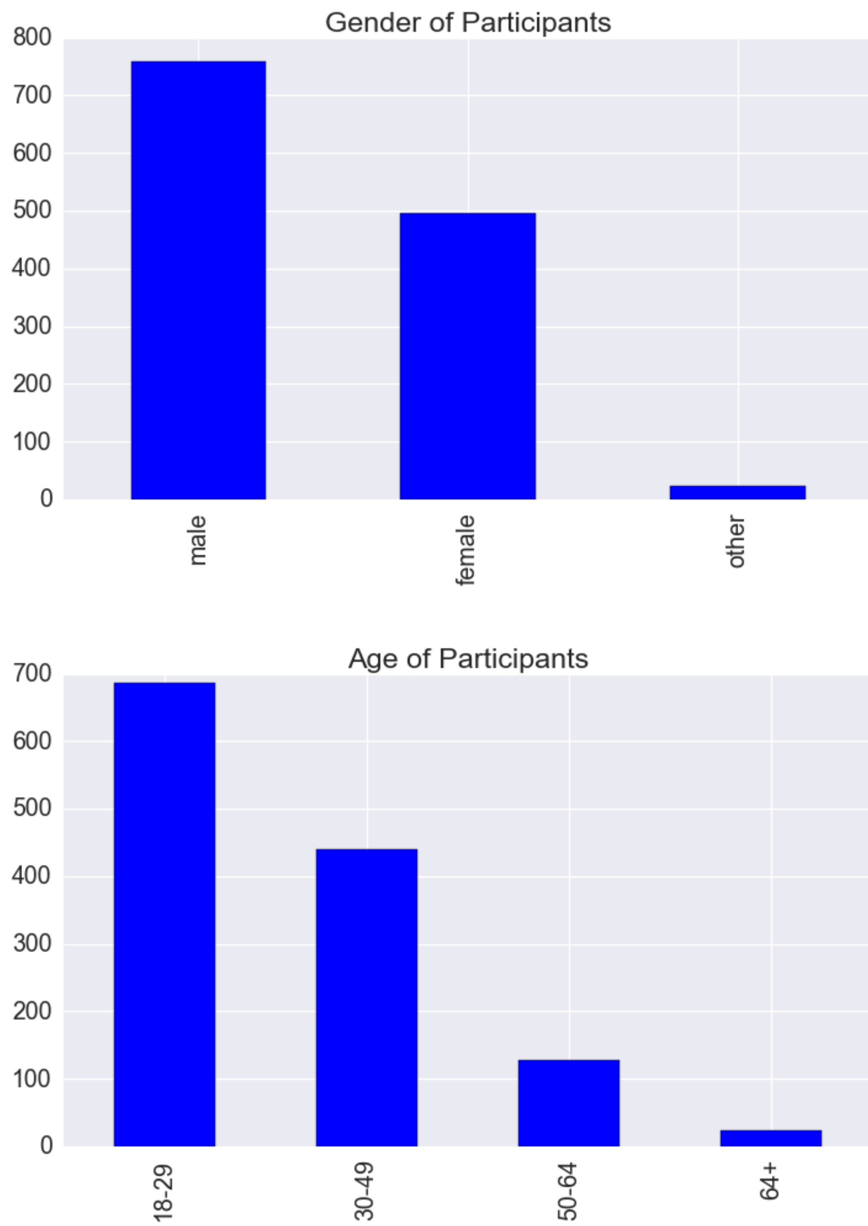


Figure 4-4: Demographics of Participants

Gender of participants were majority male. We had 758 male participants, 496 female participants and 24 signed up as "other" (it is possible that those who did not wish to identify chose the "other" category).

Majority of participants were also in age group 18-29.

4.3.2 Location

Our participants represented a wide variety of geographic locations in the US.

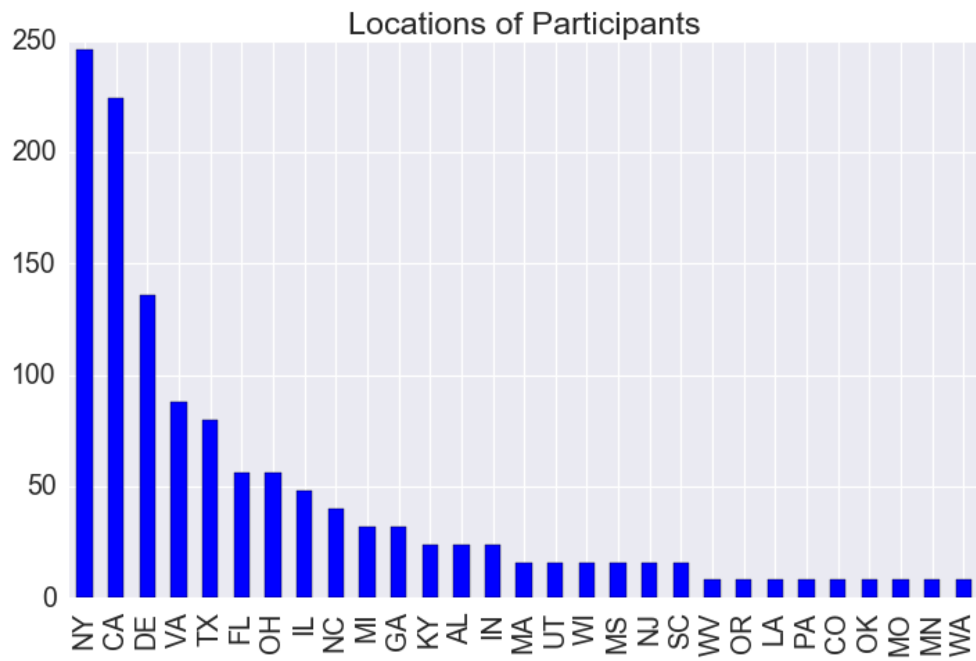


Figure 4-5: Locations of Participants

4.3.3 Political Affiliation

More than twice as many democrats than republicans particpated in our study, which also was reflected in candidate preference disparaties. These effects are taken into account in our modeling.

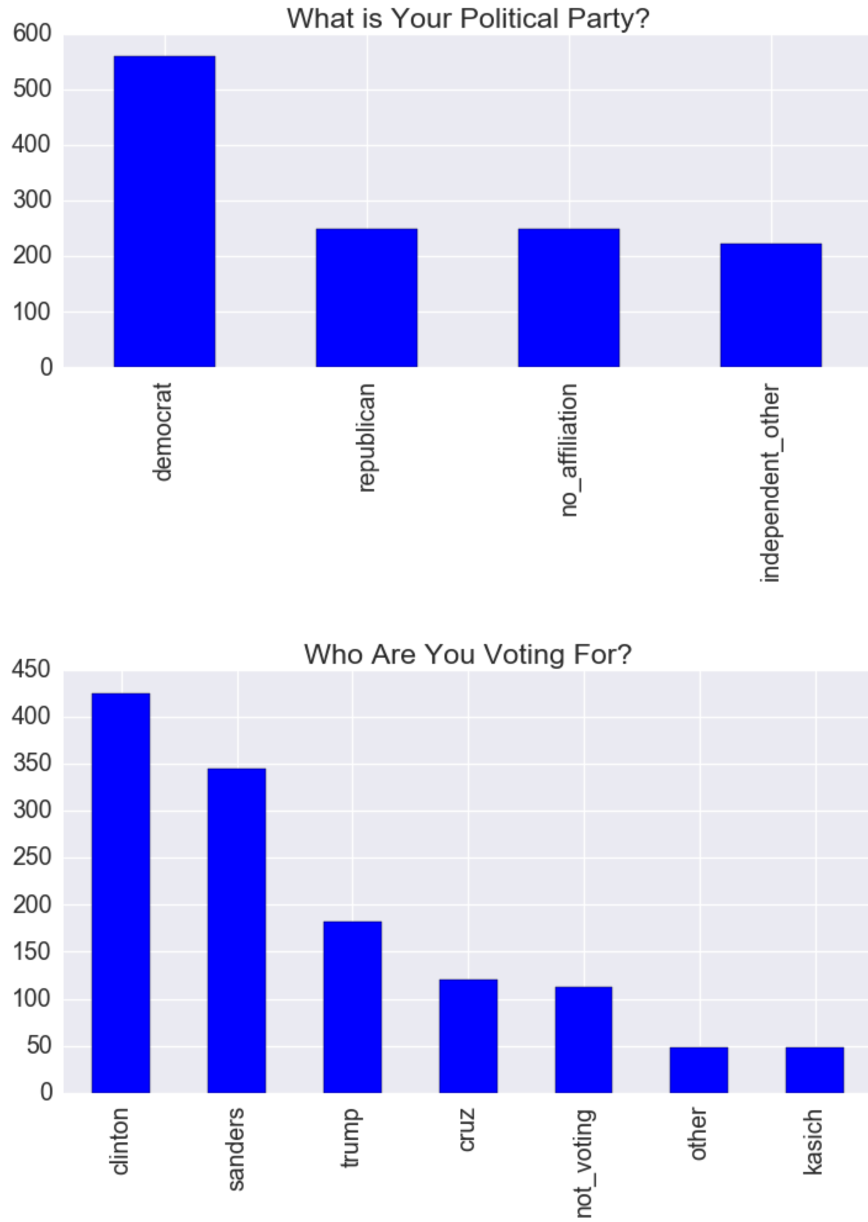


Figure 4-6: Political Affiliations of Participants

4.3.4 Trust

From a scale of -2 (Strongly Disagree) to 2 (Strongly Agree), on average, most stories were deemed trustworthy for all groups with a mean score of 0.55 (between Neutral and Agree).

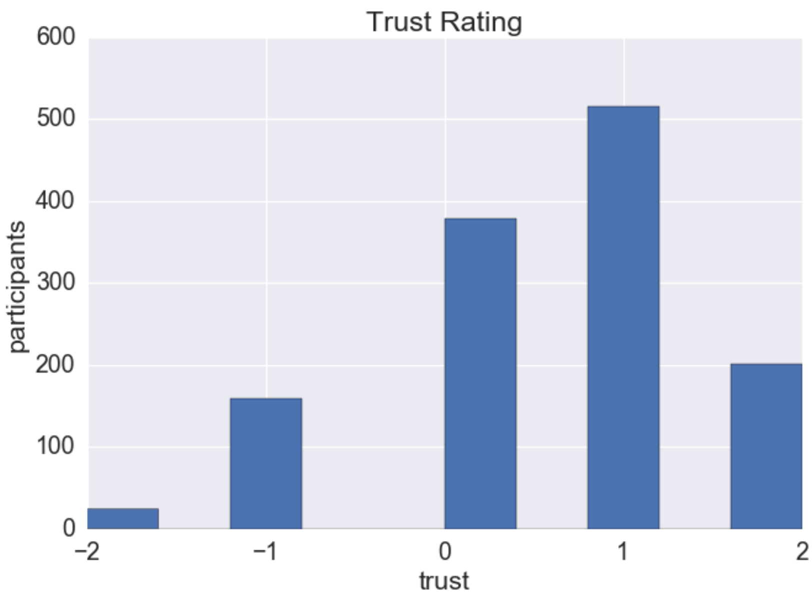


Figure 4-7: Overall Trust Ratings

However, the distrubtions for candidates varied. Stories about Sanders were seen as most trustworthy across all participants with a mean score of 0.66, followed by Cruz (0.63), Clinton (0.53), and Trump (0.40).

On average, men were slightly less likely to trust stories (average of 0.54) than women (0.60) and others.

Those in age group 30-49 were most likely to find stories trustworthy (average 0.675), followed by those in age group 50-64 (average 0.083), then those 18-29 (0.49), then those 64+ (0.083).

For distributions of trust by age group, see figure B-1 on page 106.

On average, stories were more trusted by democrats (0.69 mean).

4.3.5 Fairness

From a scale of -2 (Strongly Disagree) to 2 (Strongly Agree), on average, most stories were deemed fair for all groups with a mean score of 0.57 (between Neutral and Agree).

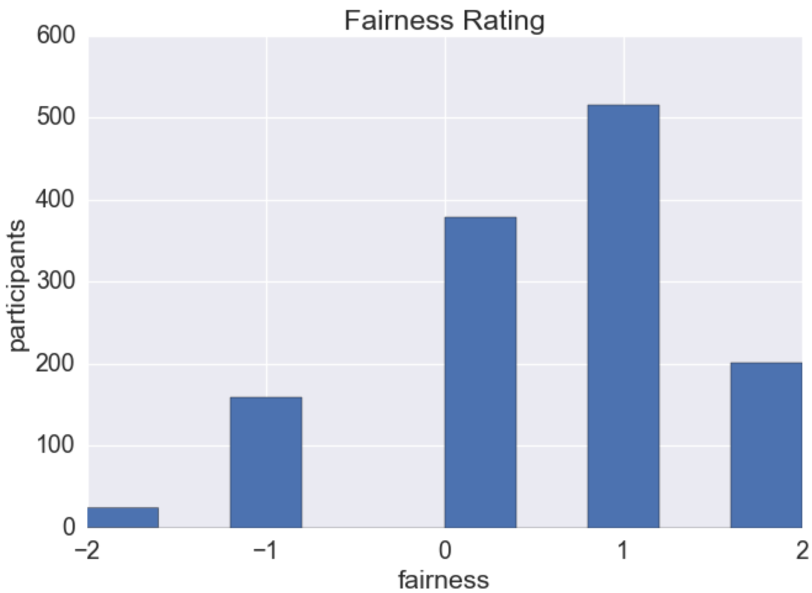


Figure 4-8: Overall Fairness Ratings

For distribution of all scores, see figure ?? on page ??.

Perceptions of fair treatment of candidates in stories diverged from the trust ratings above. Whereas stories about Sanders were most trusted, those about Clinton were seen as most fair (0.67 average).

Women were more likely to see articles as fair on average (0.67) than men (0.51 mean). Again, those in age group 30-49 were also most likely to find stories fair (average .70), this time followed by Millenials (0.51 average), then those 50-64 (0.48) and 64+ (0.20).

Democrats and Independents were far more likely to view stories as fair on average (0.68, 0.67) than Republicans (0.375), although all averages were between neutral and fair.

This finding about low perceptions of fairness in media is aligned with prior research findings. In "The Liberal Media Myth Revisited," T.T. Lee hypothesized (and verified) that "the more conservative (versus liberal) media consumers are, the more likely they are to perceive a media bias" and similarly "the more consumers lean toward the Republican (versus Democratic) party, the more likely they are to perceive a media bias" [22].

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Chapter 5

Analysis

Table 5.1: Factors Affecting Trust in News Articles

Independent Variables	β
Reading Level	1,278
Source (Fox News)	-0.45*
Reader Party (Unaffiliated)	-0.54.

*Note: N = 1,280. .p < 0.1. *p < .05. **p < .01. ***p < .001.*

5.1 Reading Level Effects

Note: this part is still brewing. I am working with one of Iyad's students to verify my statistical analysis and also trying to meet with Iyad next week just to make sure my experiment is correctly interpreted.

As of now, H1 and H2 are both not proved (looks like reading level has no significant effect). That also defaults H3 + H4 to be true.

5.2 Media Brand Effects

Preliminary results:

Using factorial ANOVA, when we model fairness as a function of story reading level $\times$ source of story $\times$ party of the candidate, we see that the source of the story has a high effect on the level of fairness perceived (F value 6.598, Pr ($>$F) 0.000201). Reading level has no significant effect. The same holds true for trust scores (F values 10.978, Pr($>$F) 4.06e-07).

One interesting observation is that showing *no source at all* has a negative effect on both trust and fairness. I am still analyzing that effect to see what it is.

Confirming hostile media effects, we see a significant effect of the reader's political affiliation aligning with the sources. We also so a significant effect if your candidate is being written about.

I'm working to try to see those two effects in comparison, which would have interesting implications for this election cycle. Would be neat to see that party loyalty is officially (significantly) broken.

5.3 Conclusions

To-do

5.4 Limitations

Our study shows significant effects that open potential new areas of experimentation while confirming past theories of how media bias is formed. In the interest of focus, our study centered around four candidates and a narrowed dataset of eight stories, but in the future could be replicated on a larger set of more diverse stories and outlets.

Furthermore, although the contributor market on CrowdFlower is not representative of any specific region or demographic, it is also not representative of the nation at large. Our dataset is skewed in terms of both demographics and political affiliation.

Part II

Sharing the News

Chapter 6

Taking Media Analysis to Another Dimension of Data

In the second part of this thesis, we extend our findings from Part One to examine how political news stories from the same time period are shared on social media. In the current digital age, broadcasting a link to friends and peers often emerges as the next logical step to reading and reacting to the news. We will focus our analysis to the social platform Twitter due to its popularity for disseminating news stories. A Pew Research survey from August 2015 showed that nearly two-thirds of adults in the U.S. who are on Twitter use the platform to get news. Government and politics emerges as the third most popular type of news to tweet about (following entertainment and sports), with 17% of tweets from the average user being about that subject [7].

Sharing news stories requires a level of activation on the part of the reader beyond passive readership; often, this trigger is emotional in nature. In 2011, researchers from the Wharton School found that the potential for a news story to go viral is partially driven by physiological arousal. By performing a large-scale analysis of articles from the New York Times coded for emotional content, they were able to find emotional factors in the text that predicted its potential to make the newspaper's "most-emailed" list [9].

The following chapters of this thesis examine this emotional relationship for political news stories covering the 2016 U.S. elections. From our studies in Part One, we were able to see that political interactions between the reader and the source of the story proved to be by far the strongest motivator of trust (or lack thereof!) in reading the news. Now, in Part Two, we look for the emotional triggers in content that transcend political boundaries in motivating readers to spread the news.

6.1 The Social Media Megaphone

In the changing landscape of both journalism and politics, social media is playing an increasingly large role in mobilizing and spreading information to citizens. President Barack Obama's win in 2008 is often attributed as the first example of a successful social media campaign in the elections. Establishing an online presence that recruited more than 3 million individual contributors and 5 million volunteers, Obama created a grassroots political movement [11]. Publicity and public sound bites matter–especially when it's free and has the potential to go viral.

This election cycle, in particular, already shows a heavy skew by social media. The New York Times estimated a 2 billion-dollar advantage in free media for Donald Trump on platforms from television to Twitter, all of which has no small impact on the messages broadcast to voters [13]. Although "free media" messages have less ability to be carefully controlled in comparison to paid advertisements, they also have more potential to reach a wider audience. Sentiments echoed by one potential voter now have the ability to be broadcast and spread to millions of others in a real-time, public sphere.

6.2 The (Short) Attention Economy

At the same time that social media has the power to create a flood of free advertising and media for political candidates, the abundance of information on the web has created new challenges and questions about the kind of content being processed by readers. This paradox– between the ease of accessibility to information and the increasingly limited bandwidth of consumers– is described as one of the challenges of being in an *attention economy* [16]. Moreover, high-impact events like the presidential elections especially intensifies this effect– about 60 % of Americans reported feeling exhausted by media coverage of the elections in July of 2016 [17]. To explore the effects of the attention economy on the reading of political news, we examine **story length** and how it relates to sharing popularity in the analysis to follow.

6.3 Negativity in Politics and the Internet

In addition, the option of anonymity and pseudo-anonymity on a social network like Twitter (along with other traits of Internet communication), is theorized to contribute to increased negative and hostile behavior, potentially increasing tension for the already-fraught subject of politics. This phenomenon, is coined as the *online disinhibition effect* [34].

In Berger and Milkman's study of story virality, it was found that *positive* content was more likely to be shared than negative content– against conventional belief [9]. Political news, however, is a unique category of news, and this election in particular– where one-in-four Americans report disliking the presidential candidates– appears to have a negative overtone.

To compare the sharing of election news stories versus patterns of general virality in the news, and to examine the extent in which negative sentiment is popular, we calculate the *negativity* of stories, and how that relates to Twitter behavior.

We also examine the effects of the degree of combined emotionality in the content and how that relates to Twitter shares, to see if either more positive or more negative content is more likely to be shared overall than content that ranks low in emotionality. Although positive content was found to be more popular than negative content in the sharing of stories, both highly positive and highly negative content was more likely to become viral, and we expect the same to hold for political news [9].

Chapter 7

Data Collection

Our main dataset is a connected corpus of news articles about the presidential elections and the tweets that share them from January 1, 2016 to May 1, 2016 over 13 news outlets. In this chapter, we detail the collection and creation of our dataset, along with the unique challenges of working with "big data".

7.1 The Electome Project

The backbone of our data collection and classification process lies under the umbrella of the Electome project, a large, collaborative effort with the Laboratory for Social Machines to examine the "horse-race of ideas" and competition of narratives during the presidential election year. The goal of the Electome project is to create novel stories for data journalists as well as technically innovative ways to examine the national conversation using machine learning and "big data" analysis through both social and traditional media coverage. The first step of both our news and Twitter data processing method uses machine learning classifiers from the Electome project.

7.2 News Dataset

7.2.1 Duration & Scope

For our news dataset, we scraped articles from the RSS feeds of news publications every hour over five months and 13 publications:

- CNN
- Fox News
- The New York Times
- The Wall Street Journal
- The Washington Post
- The Los Angeles Times
- The Associated Press
- Reuters
- McClatchy
- Politico
- Buzzfeed
- The Huffington Post
- NPR

The choices above span a mix of publications. We include sources that:

- Have mostly conservative audiences and mostly liberal audiences [26]
- Come from mixed primary media formats (television, paper, online, radio)
- Are viewed as "legacy" (over a hundred years old) and "new" media (founded online within the last 10 years)
- Focus solely on political news (Politico, McClatchy)
- Are newswire services (the Associated Press, Reuters news)

to capture a variety of types of election coverage and target audiences.

We look at stories from January 1, 2016 (the start of the election year) to May 1, 2016. This time period captures the bulk of the primary election, when coverage of multiple presidential candidate contenders creates greater variety in news stories for our analysis.

7.2.2 Data Pipeline

Articles are processed in a 3-step pipeline, pictured below.

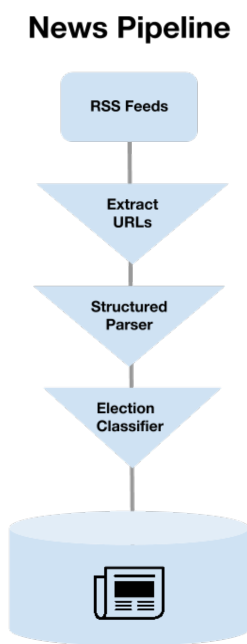

Figure 7-1: Election News Pipeline

After collecting the links to the full content of the news stories from each publication's RSS feed, we pass each link to a structured content parser that extracts entities and features from the raw HTML.

The story text is then passed into a machine learning classifier for election news from the Electome project [1].

[1]Designed and implemented by Prashanth Vijayaraghavan.

We collect and classify a total of 22,959 articles as election-related with over 80% confidence, an average of 5,700 per month and 191 per day.

7.3 Tweets Dataset

7.3.1 Duration & Scope

The Laboratory for Social Machines was founded on the premise of a research grant with Twitter which allows access to the "firehose" of all activity on Twitter. We start with the pool of all tweets between January 1, 2016 and May 1, 2016 in our data process.

7.3.2 Data Pipeline

Tweets pass through a similiar pipeline as news stories. We sort all tweets with an election classifier which has been shown to be able to detect election-related tweets with an F-score of 92% [38]. We then filter by those that share a link (which might potentially be a news story).

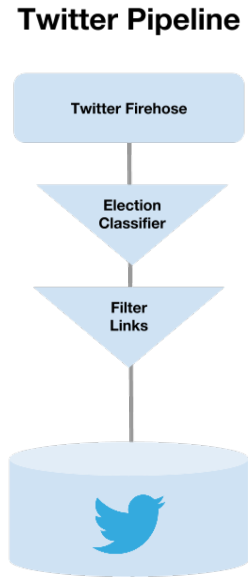

Figure 7-2: Election Tweets Pipeline

We collect and sort a total of 16,667,685 tweets as election-related and containing at least one URL in the text, an average of 4,000,000 per month and 140,000 per day.

7.4 Combined Dataset

The final step of our data collection process is to extract, expand and connect the links shared in our election-related tweets with articles in our database.

7.4.1 Mapping Tweets to Stories

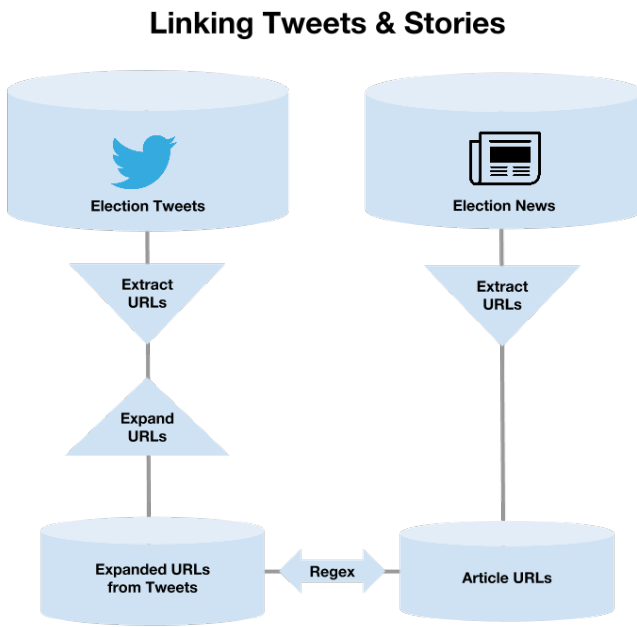

Figure 7-3: Data Pipeline

Twitter automatically formats all links into a shortened "t.co" format, so we first expand all links in tweets (16.6 million), then use a regular expression to see if the final destination of the expanded link matches a query-truncated URL of a story in our database. We checked the validity of 382 billion url-story matches in less than a day by running the processes on the Amazon Web Services cloud computing platform in parallel using the Gnu-parallel command line tool [36].

7.4.2 Final Corpus

In total, we found that 30% of the election stories we tracked were shared on Twitter during the time period of January 1st through May 1st.

There were 137,986 tweets that contained a link to 6,911 unique stories (out of 22,960).

Since we chose the story to be the unit of analysis in this thesis, we then eliminated any stories that were shared by less than 10 tweets.

This left a total of 2,650 distinct articles (38%) shared in 123,113 (89%) tweets by 20,956 Twitter users (93%).

7.4.3 Descriptive Findings

The vast majority of stories are shared less than 100 times.

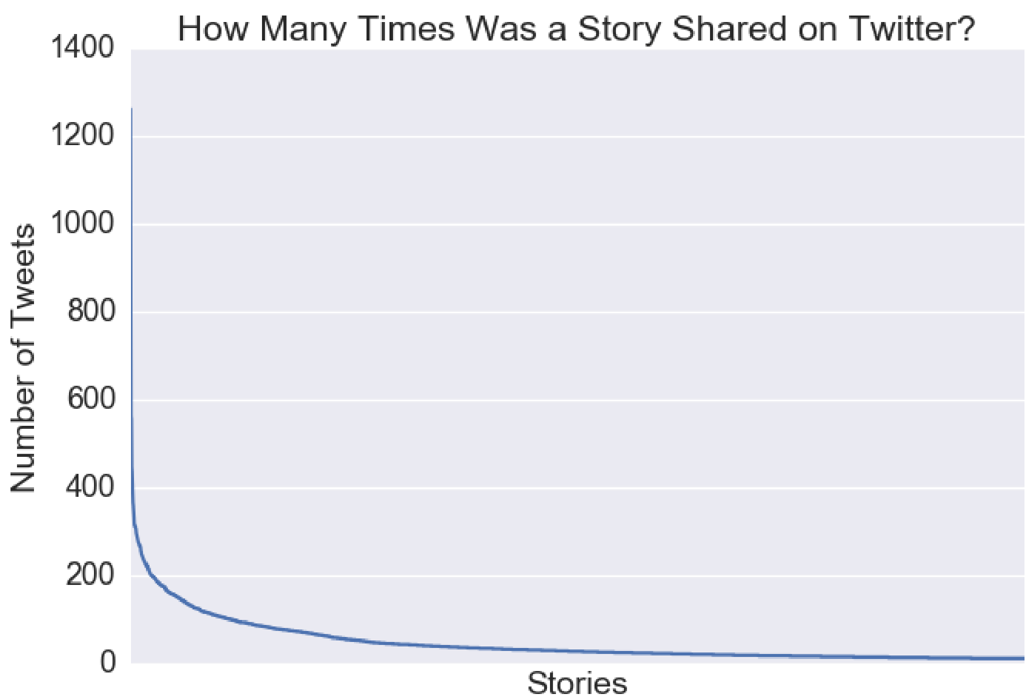

Figure 7-4: Distribution of Story Shares

Story sharing behavior follows an approximate power law distribution. On average, stories are shared 46 times, however, the median (50th percentile) of shares is just 26.

CNN, Politico, and Fox lead in publication popularity with the highest number of stories shared by tweets in our dataset– likely due to the volume and close association to political content of the companies. Because our data pipeline detailed in the previous chapter looks for election-related news, outlets which track the campaign extensively are more likely to show up in our results.

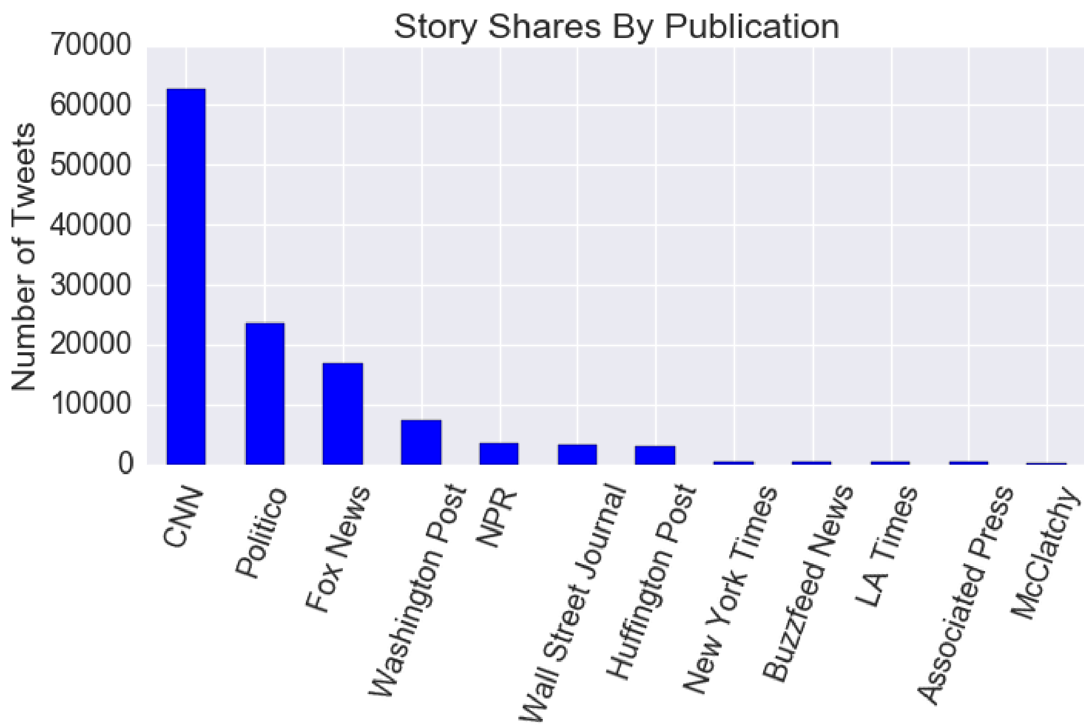

Figure 7-5: Number of story shares by publication

Article	# tweets
The One Weird Trait That Predicts Whether You're a Trump Supporter	1260
Donald Trump Is Shocking, Vulgar and Right	901
Biden praises Sanders on income inequality	563
Why I'm voting for Trump	554
Anne Frank's stepsister compares Donald Trump to Adolf Hitler	445
Trump basks in his spotlight	436
Rubio: Law-abiding undocumented immigrants could stay	413
Terrorists use Trump's 'Muslim ban' speech in recruitment video	398
Iowa caucuses: Donald Trump's moment of truth	364
GOP senators: If Cruz wins, we lose	357

Table 7.1: Top 10 Shared Stories

Examining the top 10 most shared stories, it comes as no surprise that outsized personality Donald Trump is by far the most "tweetable" candidate, dominating the list with 7 out of 10 stories featuring his name in the title.

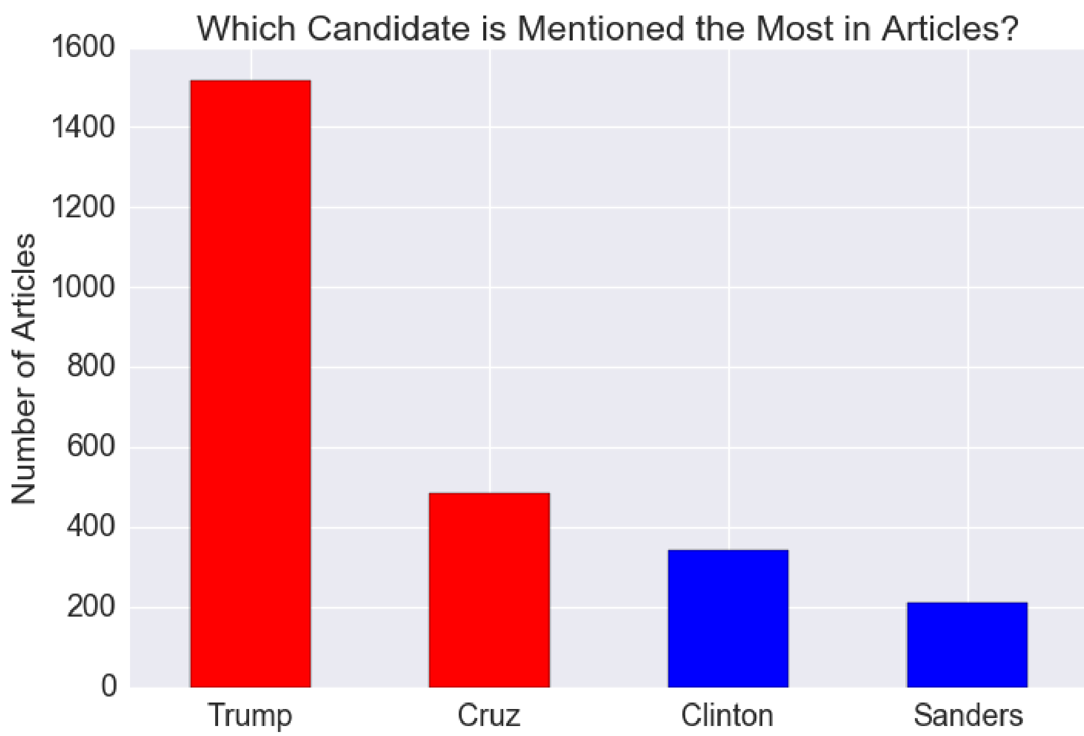

Figure 7-6: Most frequently mentioned candidate in stories

The *extent* to which he is prominent in articles is clear: by coding each story by the most frequently mentioned candidate, Trump has nearly three times as much coverage at nearly 60% as the runner-ups, Ted Cruz and Hillary Clinton.

The large number of stories with Cruz as the most-mentioned candidate are likely due to his association to Trump as a Republican runner-up: 96% of stories where Cruz is the most-mentioned candidate feature Trump as the second-most frequently occuring.

Chapter 8

Metrics for Political and Emotional Engagement

In the following sections, we discuss the tools and methods that we use to analyze our independent variables.

8.1 Emotional Coding

For the emotional coding of news articles, we use dictionaries from the Harvard General Inquirer, a lexicon that is popular for computerized content analysis [33]. The Inquirer is a public-use alternative to the LIWC system, which in Berger and Milkman's study of online virality showed results that were significantly positively correlated with the output of manual coding [9]. In particular, we use the *Positiv* and *Negativ* collections, a set of 1,915 well-established words signifying positive outlook (not including words for *yes*) and 2,291 words signifying negative outlook (not including words for *no*), respectively. Repeating the same metrics from *What Makes Online Content Viral?*, we quantify for each document:

$$emotionality = \frac{count(positiv \mid negativ)}{count(words)}$$

$$positivity = \frac{count(positiv)}{count(words)} - \frac{count(negativ)}{count(words)}$$

as independent variables in our analysis.

8.2 Followership as a Proxy for Political Engagement

In the following sections, we use Twitter followership as a proxy for measuring degrees of political engagement.

Previous research in network analysis and attempts to predict latent political affiliations of users in the social network has shown that users on Twitter tend to show network homophily within political groups, and that "like follows like" [12]. In addition, followership of only Democratic or only Republican official accounts can be used as a reasonable estimator of party loyalty. Those accounts that follow only the officials of one party tend to demonstrate more closeness with other users in their political party than those who do not.

Due to the highly individual nature of this election, where candidate loyalty does not necessarily imply goodwill towards the party, we look specifically at what candidates users follow instead of party loyalty at large.

For general *levels* of political engagement, we look at the number of political candidates a Twitter user follows as a proxy for how likely they are to share political news.

In addition, for single-candidate Tweeters, we divide users by the candidate they follow. At the time of data collection completion (May 1, 2016), the top two candidates by delegate count in each party were Hillary Clinton (D), Bernie Sanders (D) and

Donald Trump (R) and Ted Cruz (R), so we split users into these four groups.

8.2.1 A Look at Candidate Followership

Our dataset contains 6,406 unique single-candidate Twitter users. Trump-only followers lead with about 31%, followed closely by Clinton-only (29%), then Sanders (25%) and Cruz (14%).

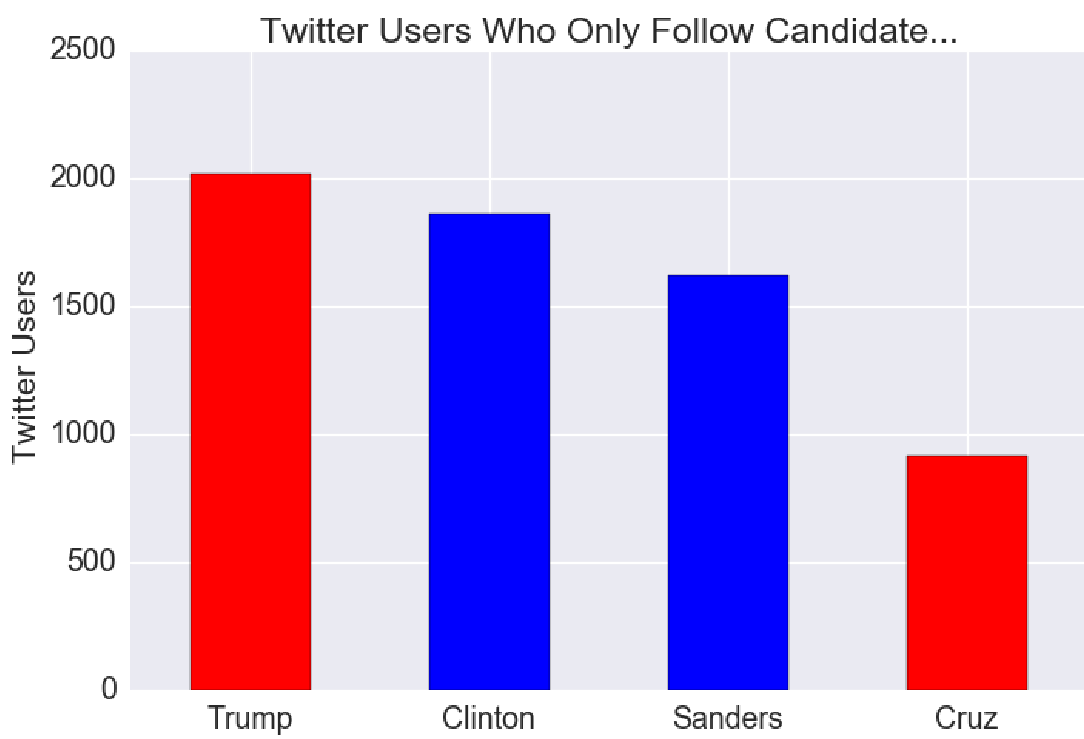

Figure 8-1: Number of Tweets by Each Segment

Trump's free media advantage becomes clear when looking at the *volume* of tweets each group of users tweet: 37% of tweets sharing articles come from Trump-only followers versus 27% for Clinton-only, 20% for Sanders-only, and 14.6% for Cruz.

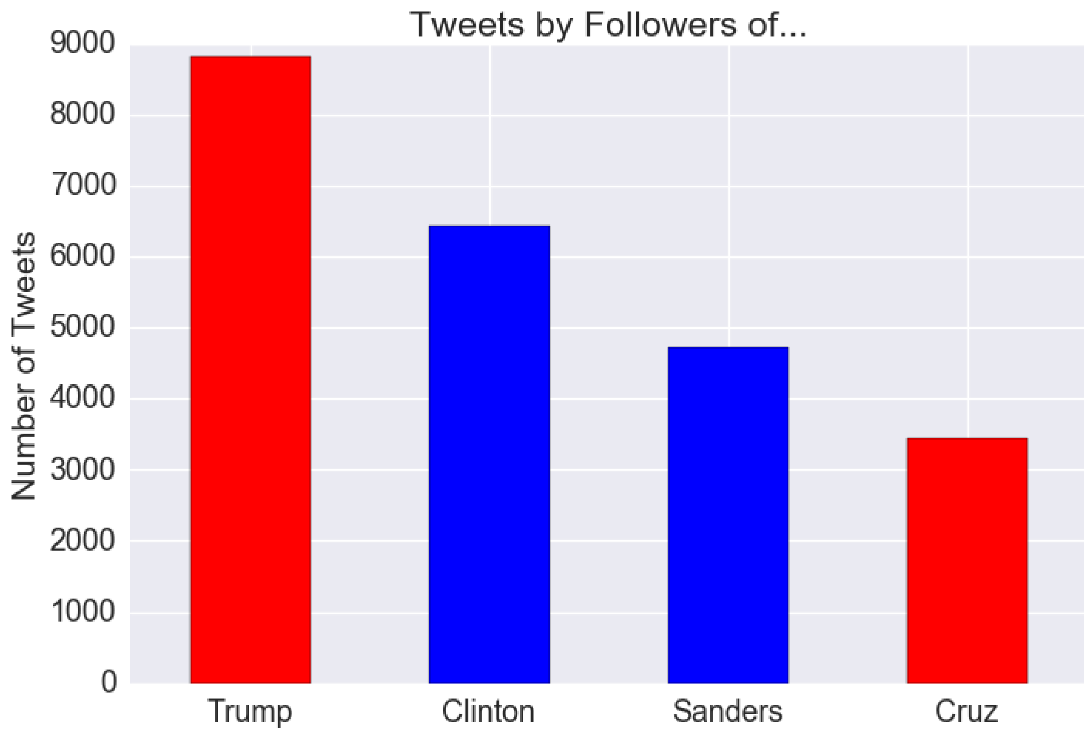

Figure 8-2: Most frequently mentioned candidate in stories

Although candidate-followership is only a proxy for the latent variable of candidate loyalty, we are observe the nature of the content being shared by each group. Again, across all four segments, Republican candidate Trump leads the top number of mentions in stories shared.

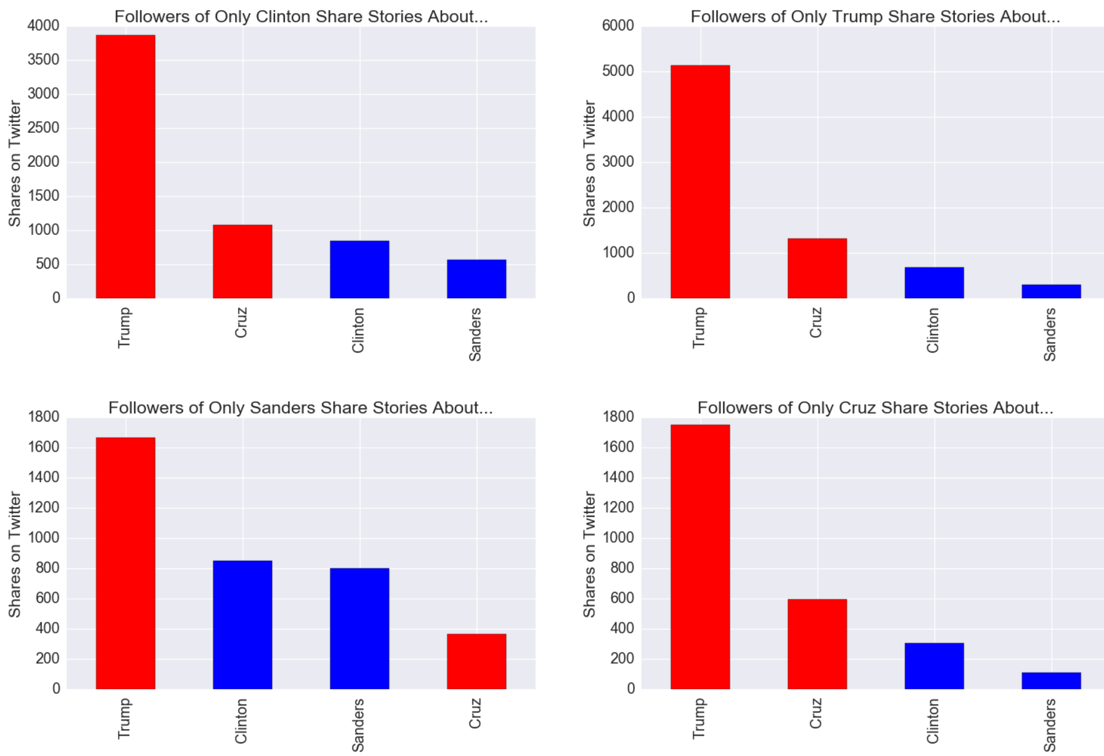

Figure 8-3: Tweet and User Counts by Followership

8.2.2 A Look at Levels of Political Engagement

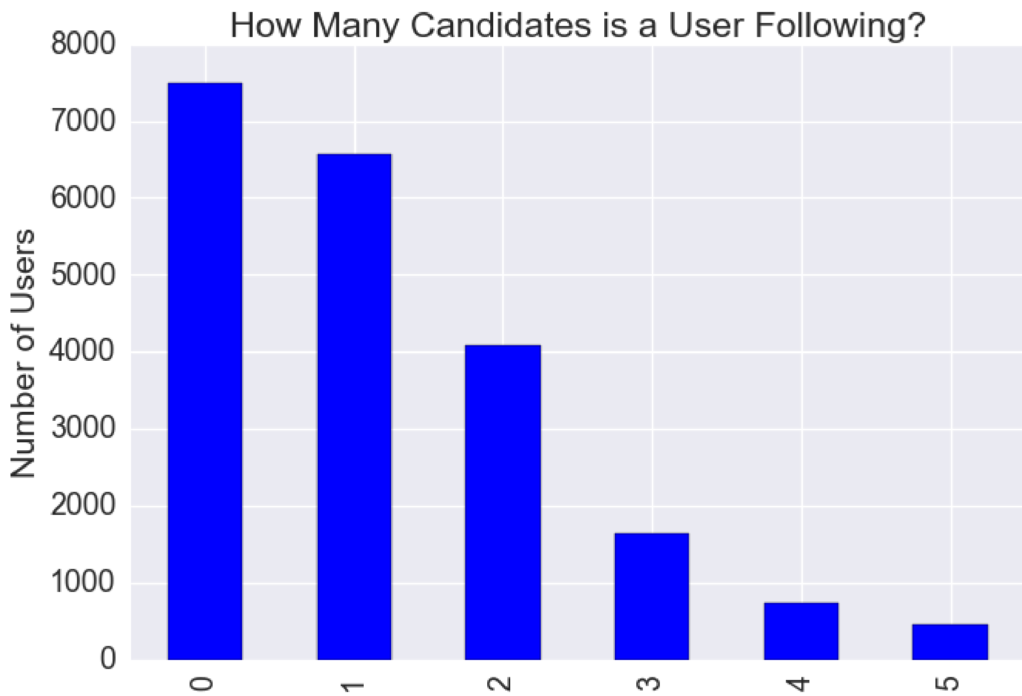

Figure 8-4: Number of candidates followed

36% of Twitter users in our dataset follow none of the four political candidates, followed by 31% who follow one candidate, 20% who follow two, and 13% who follow three or more candidates.

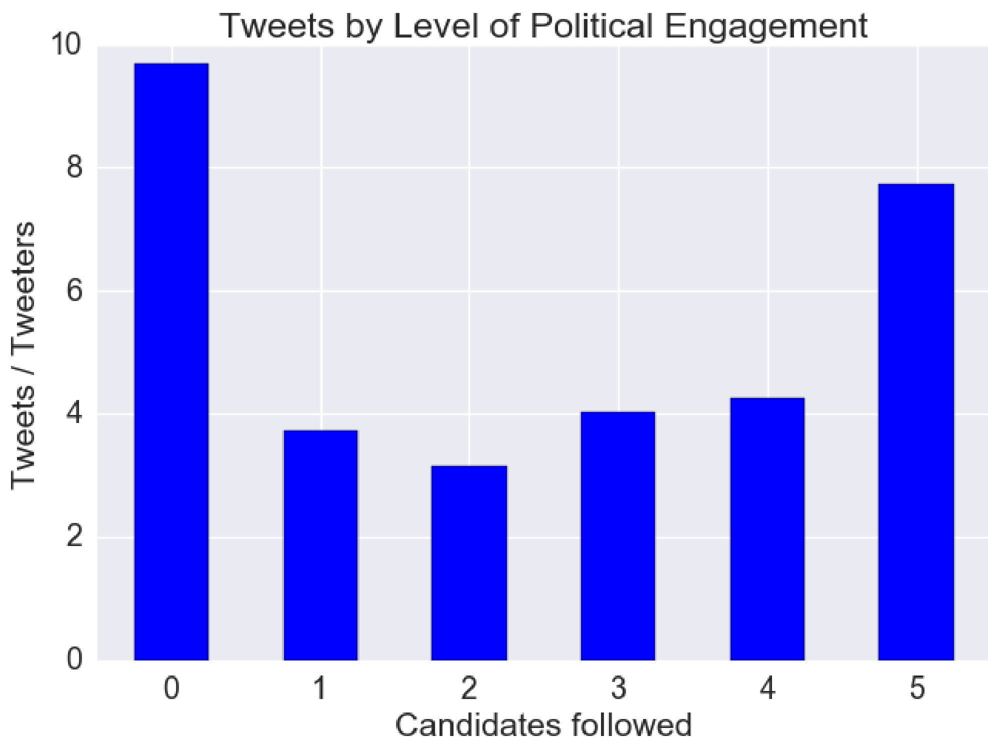

Figure 8-5: Ratio of Tweets to political candidates followed

We see a U-shaped curve between the number of candidates followed (level of observed political engagement) and the ratio of political news tweets per user.

In the following analyses, we segment levels of political engagement into three groups for the sake of comparison:

- *the unaffiliated* (those who follow no presidential candidates, but do tweet about political news)
- *single-candidate* Tweeters (those who follow one and only one presidential candidate, and tweet about political news)
- *political aficionados* (those who follow all 4 (or more) candidates, and tweet about political news)

Chapter 9

Analysis

In this chapter, we test for correlations between the metrics defined in Chapter 9 and popularity of a story on Twitter.

9.1 Hypotheses

Re-iterating from Chapter 7, the focus of Part II of this thesis is to examine how emotionally evocative text in an article relates to the way it is shared on Twitter. In addition, we look at the effects of story length on its popularity as a baseline to confirm theories of attention on the Internet.

We hypothesize the following behavior in our dataset of stories and tweets:

- **H1:** Story length has a *negative* correlation with Twitter shares, due to the effects of the Internet attention economy and overexposure to political media [16].

- **H2:** Emotionality has a *positive* correlation with Twitter shares, consistent for viral content in general [9].

- **H3:** Positivity has a *negative* correlation with Twitter shares, due to the nature of political news and contrary to generalized findings [9]

For each of these three independent variables (story length, emotionality, positivity) we repeat analyses across three views of the data: first, the entire dataset; then, by political candidate followed amongst users who follow only one candidate; and finally, by the number of political candidates followed (degree of political engagement), to look for differences amongst different populations of political tweeters.

9.2 Methodology

Since our dependent variable, tweet volume, is a set of discrete counts that are positively truncated, we use negative binomial regression models for our analysis [31]. The distribution of tweet volume is not a normal distribution, and it is not recommended to perform a log transformation on count data to fit it to an OLS regression unless there is little dispersion in the data [28]. Poisson models are a subset of negative binomial models without the dispersion parameter. Below, we see that the negative binomial model provides the best fit and that our data is overdispersed, as the dispersion parameter θ is greater than 1.

In each case, we compare our findings to those using plain linear and Poisson regression models and are able to achieve the same significant results.

9.3 All Data

Table 9.1: Tweet Volume vs. Story Length, All Data

	Dependent variable:		
	Number of Tweets		
	OLS	*Poisson*	*negative binomial*
	(1)	(2)	(3)
Story length	-0.004^{***}	-0.0001^{***}	-0.0001^{***}
	(0.001)	(0.00000)	(0.00002)
Constant	50.426^{***}	3.936^{***}	3.895^{***}
	(1.819)	(0.005)	(0.027)
Observations	2,650	2,650	2,650
R^2	0.003		
Adjusted R^2	0.003		
Log Likelihood		$-65,042.390$	$-12,778.740$
θ			1.346^{***} (0.034)
Akaike Inf. Crit.		130,088.800	25,561.490
Residual Std. Error	60.156 (df = 2648)		
F Statistic	8.452^{***} (df = 1; 2648)		
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 9.2: Tweet Volume vs. Emotionality, All Data

	Dependent variable:		
	Number of Tweets		
	OLS	*Poisson*	*negative binomial*
	(1)	(2)	(3)
Emotionality	305.229^{**}	6.111^{***}	6.019^{***}
	(122.427)	(0.276)	(1.777)
Constant	40.349^{***}	3.714^{***}	3.716^{***}
	(2.685)	(0.006)	(0.039)
Observations	2,650	2,650	2,650
R^2	0.002		
Adjusted R^2	0.002		
Log Likelihood		−65,180.470	−12,779.510
θ			1.345^{***} (0.034)
Akaike Inf. Crit.		130,364.900	25,563.030
Residual Std. Error	60.181 (df = 2648)		
F Statistic	6.216^{**} (df = 1; 2648)		
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 9.3: Tweet Volume vs. Positivity, All Data

	Dependent variable:		
	Number of Tweets		
	OLS	*Poisson*	*negative binomial*
	(1)	(2)	(3)
Positivity	-281.010^{**}	-6.029^{***}	-5.391^{***}
	(139.546)	(0.338)	(2.029)
Constant	47.078^{***}	3.851^{***}	3.849^{***}
	(1.221)	(0.003)	(0.018)
Observations	2,650	2,650	2,650
R^2	0.002		
Adjusted R^2	0.001		
Log Likelihood		−65,253.640	−12,781.640
θ			1.343^{***} (0.034)
Akaike Inf. Crit.		130,511.300	25,567.270
Residual Std. Error	60.206 (df = 2648)		
F Statistic	4.055^{**} (df = 1; 2648)		
Note:			*p<0.1; **p<0.05; ***p<0.01

9.4 By Degree of Political Engagement

In the our analyses, we segment levels of political engagement into three groups for the sake of comparison:

- *The unaffiliated* (those who follow no presidential candidates, but do tweet about political news)
- *Single-candidate* followers (those who follow one and only one presidential candidate, and tweet about political news)
- *Political aficionados* (those who follow all 4 (or more) candidates, and tweet about political news)

We repeat the same methods and variables in determining our correlations. For the sake of brevity, all tables and comparisons of all three models (OLS, Poisson, NB model) can be found in Appendix A, tables A.1 - A.9.

Overall, we find that:

Unaffiliated tweeters show the same patterns as the general dataset with a negative correlation between story length and Twitter shares ($\beta = -0.003$, $p < 0.01$), positive correlation between emotionality and Twitter shares ($\beta = 7.427$, $p < 0.01$), and a negative correlation between positivity and Twitter shares ($\beta = -4.036$, $p < 0.01$).

Single-candidate followers, on the other hand, show a slight positive correlation between story length and number of Twitter shares ($\beta = 0.0002$, $p < 0.01$). We hypothesize that if following a single candidate can serve as a proxy for candidate loyalty, then perhaps the correlation signifies a willingness to read and share more complex content on behalf of the candidate and a deeper degree of political involvement.

We see the same effects for the *political aficionados* group, again, a small but significant positive correlation between story length and number of tweets ($\beta = 0.0003$,

$p < 0.01$). Again, this suggests a potential difference in levels of engagement with political news.

9.5 By Candidate

9.5.1 Trump-Only Followers

9.5.2 Clinton-Only Followers

9.5.3 Sanders-Only Followers

9.5.4 Cruz-Only Followers

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Chapter 10

Conclusion

10.1 Summary of Findings

Overall, we verify the hypotheses that we propose in Chapter 9, and find that, on the whole:

- Shorter stories are more likely to be shared on Twitter
- Stories high in emotional words, both negative and positive, are more likely to be shared on Twitter
- Stories that are less positive are more likely to be shared on Twitters

These results confirm our expectations of reader attention on the Internet, the emotional nature of content virality, and the negative connotation of political media.

We were able to see small but significant differences in the number of political candidates a user followed and the length of the stories that were likely to be shared, suggesting differing degrees of political involvement. However, we were unable to find many significant differences between segments by specific political candidates that users followed.

This suggests that either the characteristics of political news we examine (length, emotionality, positivity) are universal in their effects on motivating readers to share articles, or that our methods of dividing Twitter users do not reveal significant underlying differences between readers.

10.2 Limitations & Future Work

Although we take a "big data" approach to our analyses, our dataset is by no means a complete mapping of *all* political news sharing activity on Twitter. Our sources are limited to a small but diverse set of publications, which are by no means representative of all news outlets.

Furthermore, we match tweets with stories optimizing for efficiency and speed by using regular expressions, rather than completeness.

Potential paths of future research include:

- Expanding the set of publications tracked (currently underway under the Electome project)
- Replicating the analysis on a real-time basis
- Using machine learning methods to match tweets with stories in a more intelligent way
- Analyzing more nuanced emotive words in the text, in addition to positive and negative words
- Looking at additional signals in the Twitter data, such as user characteristics of the sharer and network aspects of stories being shared
- Segmenting Twitter users in different ways aside from candidates followed

Still, our analysis provides a first view of article sharing on Twitter in a unique and eventful election year with large responses on social media.

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Chapter 11

Final Remarks

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Appendix A

Tables

Table A.1: Tweet Volume vs. Story Length, the Unaffiliated

	Dependent variable:		
	Number of Tweets		
	OLS	*Poisson*	*negative binomial*
	(1)	(2)	(3)
Story length	-0.008^{***}	-0.0004^{***}	-0.0003^{***}
	(0.001)	(0.00001)	(0.00002)
Constant	35.299^{***}	3.683^{***}	3.605^{***}
	(1.168)	(0.006)	(0.031)
Observations*	2,640	2,640	2,640
R^2	0.029		
Adjusted R^2	0.028		
Log Likelihood		−49,432.820	−11,415.510
θ			0.954^{***} (0.024)
Akaike Inf. Crit.		98,869.640	22,835.020
Residual Std. Error	38.604 (df = 2638)		
F Statistic	77.414^{***} (df = 1; 2638)		
Note:			*p<0.1; **p<0.05; ***p<0.01;

* *We exclude stories not shared by this population.*

Table A.2: Tweet Volume vs. Emotionality, the Unaffiliated

	Dependent variable:		
	Number of Tweets		
	OLS	*Poisson*	*negative binomial*
	(1)	(2)	(3)
Emotionality	248.768***	8.165***	7.427***
	(79.579)	(0.347)	(2.145)
Constant	22.519***	3.147***	3.162***
	(1.747)	(0.008)	(0.047)
Observations*	2,640	2,640	2,640
R^2	0.004		
Adjusted R^2	0.003		
Log Likelihood		−51,967.750	−11,419.630
θ			0.928*** (0.023)
Akaike Inf. Crit.		103,939.500	22,843.260
Residual Std. Error	39.094 (df = 2638)		
F Statistic	9.772*** (df = 1; 2638)		
Note:			*p<0.1; **p<0.05; ***p<0.01

* *We exclude stories not shared by this population.*

Table A.3: Tweet Volume vs. Positivity, the Unaffiliated

	Dependent variable:		
	Number of Tweets		
	OLS	*Poisson*	*negative binomial*
	(1)	(2)	(3)
Positivity	−145.324	-5.277^{***}	-4.036^{*}
	(90.790)	(0.440)	(2.452)
Constant	27.797^{***}	3.324^{***}	3.321^{***}
	(0.795)	(0.004)	(0.021)
Observations*	2,640	2,640	2,640
R^2	0.001		
Adjusted R^2	0.001		
Log Likelihood		−52,150.640	−11,424.900
θ			0.925^{***} (0.023)
Akaike Inf. Crit.		104,305.300	22,853.790
Residual Std. Error	39.147 (df = 2638)		
F Statistic	2.562 (df = 1; 2638)		
Note:			*p<0.1; **p<0.05; ***p<0.01

* *We exclude stories not shared by this population.*

Table A.4: Tweet Volume vs. Story Length, Single-Candidate Followers

	Dependent variable:		
	Number of Tweets		
	OLS	*Poisson*	*negative binomial*
	(1)	(2)	(3)
Story length	0.002***	0.0001***	0.0002***
	(0.0004)	(0.00001)	(0.00002)
Constant	7.979***	2.135***	2.080***
	(0.467)	(0.009)	(0.028)
Observations*	2,581	2,581	2,581
R^2	0.007		
Adjusted R^2	0.006		
Log Likelihood		−17,969.510	−8,449.973
θ			1.330*** (0.039)
Akaike Inf. Crit.		35,943.020	16,903.950
Residual Std. Error	15.242 (df = 2579)		
F Statistic	17.223*** (df = 1; 2579)		
Note:			*p<0.1; **p<0.05; ***p<0.01

* *We exclude stories not shared by this population.*

Table A.5: Tweet Volume vs. Emotionality, Single-Candidate Followers

	Dependent variable:		
	Number of Tweets		
	OLS	*Poisson*	*negative binomial*
	(1)	(2)	(3)
Emotionality	41.896	4.211***	4.821**
	(31.596)	(0.638)	(1.917)
Constant	8.640***	2.164***	2.152***
	(0.691)	(0.014)	(0.042)
Observations*	2,581	2,581	2,581
R^2	0.001		
Adjusted R^2	0.0003		
Log Likelihood		−18,113.130	−8,470.986
θ			1.309*** (0.038)
Akaike Inf. Crit.		36,230.260	16,945.970
Residual Std. Error	15.288 (df = 2579)		
F Statistic	1.758 (df = 1; 2579)		
Note:			*p<0.1; **p<0.05; ***p<0.01

* *We exclude stories not shared by this population.*

Table A.6: Tweet Volume vs. Positivity, Single-Candidate Followers

	Dependent variable:		
	Number of Tweets		
	OLS	*Poisson*	*negative binomial*
	(1)	(2)	(3)
Positivity	-70.477^{*}	-7.387^{***}	-8.385^{***}
	(36.056)	(0.758)	(2.202)
Constant	9.643^{***}	2.264^{***}	2.267^{***}
	(0.314)	(0.007)	(0.019)
Observations*	2,581	2,581	2,581
R^2	0.001		
Adjusted R^2	0.001		
Log Likelihood		−18,087.190	−8,467.366
θ			1.313^{***} (0.038)
Akaike Inf. Crit.		36,178.390	16,938.730
Residual Std. Error	15.282 (df = 2579)		
F Statistic	3.821^{*} (df = 1; 2579)		
Note:			*p<0.1; **p<0.05; ***p<0.01

* *We exclude stories not shared by this population.*

Table A.7: Tweet Volume vs. Story Length, Political Aficionados

	Dependent variable:		
	Number of Tweets		
	OLS	*Poisson*	*negative binomial*
	(1)	(2)	(3)
Story length	0.001^{***}	0.0001^{***}	0.0003^{***}
	(0.0001)	(0.00001)	(0.00002)
Constant	2.578^{***}	1.111^{***}	0.963^{***}
	(0.147)	(0.016)	(0.030)
Observations*	1,841	1,841	1,841
R^2	0.039		
Adjusted R^2	0.038		
Log Likelihood		−5,087.030	−4,213.885
θ			2.390^{***} (0.120)
Akaike Inf. Crit.		10,178.060	8,431.769
Residual Std. Error	3.985 (df = 1839)		
F Statistic	74.279^{***} (df = 1; 1839)		
Note:			*p<0.1; **p<0.05; ***p<0.01

* *We exclude stories not shared by this population.*

Table A.8: Tweet Volume vs. Emotionality, Political Aficionados

	Dependent variable:		
	Number of Tweets		
	OLS	*Poisson*	*negative binomial*
	(1)	(2)	(3)
Emotionality	−10.483	−3.055**	−3.154
	(10.496)	(1.419)	(2.254)
Constant	3.766***	1.329***	1.331***
	(0.224)	(0.030)	(0.048)
Observations*	1,841	1,841	1,841
R^2	0.001		
Adjusted R^2	−0.00000		
Log Likelihood		−5,193.447	−4,274.369
θ			2.194*** (0.107)
Akaike Inf. Crit.		10,390.890	8,552.738
Residual Std. Error	4.064 (df = 1839)		
F Statistic	0.998 (df = 1; 1839)		
Note:			*p<0.1; **p<0.05; ***p<0.01

* *We exclude stories not shared by this population.*

Table A.9: Tweet Volume vs. Positivity, Political Aficionados

	Dependent variable:		
	Number of Tweets		
	OLS	*Poisson*	*negative binomial*
	(1)	(2)	(3)
Positivity	−19.143	−5.333***	−5.588**
	(12.417)	(1.604)	(2.620)
Constant	3.610***	1.283***	1.283***
	(0.099)	(0.013)	(0.021)
Observations*	1,841	1,841	1,841
R^2	0.001		
Adjusted R^2	0.001		
Log Likelihood		−5,190.338	−4,273.139
θ			2.198*** (0.107)
Akaike Inf. Crit.		10,384.670	8,550.278
Residual Std. Error	4.063 (df = 1839)		
F Statistic	2.377 (df = 1; 1839)		
Note:			*p<0.1; **p<0.05; ***p<0.01

* *We exclude stories not shared by this population.*

Table A.10: Tweet Volume vs. Story Length, Trump-Only Followers

	Dependent variable:		
	Number of Tweets		
	OLS	*Poisson*	*negative binomial*
	(1)	(2)	(3)
Story length	−0.0001	−0.00002	−0.00001
	(0.0002)	(0.00001)	(0.00003)
Constant	4.511***	1.507***	1.505***
	(0.292)	(0.017)	(0.036)
Observations*	1,983	1,983	1,983
R^2	0.00005		
Adjusted R^2	−0.0005		
Log Likelihood		−8,618.739	−5,135.174
θ			1.212*** (0.044)
Akaike Inf. Crit.		17,241.480	10,274.350
Residual Std. Error	8.336 (df = 1981)		
F Statistic	0.095 (df = 1; 1981)		
Note:			*p<0.1; **p<0.05; ***p<0.01

* *We exclude stories not shared by this population.*

Table A.11: Tweet Volume vs. Emotionality, Trump-Only Followers

	Dependent variable:		
	Number of Tweets		
	OLS	*Poisson*	*negative binomial*
	(1)	(2)	(3)
Emotionality	18.472	3.935***	4.163*
	(20.204)	(1.086)	(2.459)
Constant	4.080***	1.413***	1.409***
	(0.438)	(0.024)	(0.054)
Observations*	1,983	1,983	1,983
R^2	0.0004		
Adjusted R^2	−0.0001		
Log Likelihood		−8,613.202	−5,133.927
θ			1.214*** (0.045)
Akaike Inf. Crit.		17,230.400	10,271.850
Residual Std. Error	8.334 (df = 1981)		
F Statistic	0.836 (df = 1; 1981)		
Note:			*p<0.1; **p<0.05; ***p<0.01

* *We exclude stories not shared by this population.*

Table A.12: Tweet Volume vs. Positivity, Trump-Only Followers

	Dependent variable:		
	Number of Tweets		
	OLS	*Poisson*	*negative binomial*
	(1)	(2)	(3)
Positivity	-68.264^{***}	-15.234^{***}	-14.692^{***}
	(24.057)	(1.347)	(2.971)
Constant	4.608^{***}	1.521^{***}	1.520^{***}
	(0.196)	(0.011)	(0.024)
Observations*	1,983	1,983	1,983
R^2	0.004		
Adjusted R^2	0.004		
Log Likelihood		−8,556.939	−5,122.437
θ			1.229^{***} (0.045)
Akaike Inf. Crit.		17,117.880	10,248.880
Residual Std. Error	8.319 (df = 1981)		
F Statistic	8.052^{***} (df = 1; 1981)		
Note:			*p<0.1; **p<0.05; ***p<0.01

* *We exclude stories not shared by this population.*

Table A.13: Tweet Volume vs. Story Length, Clinton-Only Followers

	Dependent variable:		
	Number of Tweets		
	OLS	*Poisson*	*negative binomial*
	(1)	(2)	(3)
Story length	0.0003***	0.0001***	0.0001***
	(0.0001)	(0.00001)	(0.00002)
Constant	2.941***	1.106***	1.091***
	(0.168)	(0.017)	(0.030)
Observations*	1,964	1,964	1,964
R^2	0.003		
Adjusted R^2	0.003		
Log Likelihood		−5,643.146	−4,425.975
θ			2.066*** (0.095)
Akaike Inf. Crit.		11,290.290	8,855.950
Residual Std. Error	4.909 (df = 1962)		
F Statistic	6.750*** (df = 1; 1962)		
Note:			*p<0.1; **p<0.05; ***p<0.01

* *We exclude stories not shared by this population.*

Table A.14: Tweet Volume vs. Emotionality, Clinton-Only Followers

	Dependent variable:		
	Number of Tweets		
	OLS	*Poisson*	*negative binomial*
	(1)	(2)	(3)
Emotionality	24.727**	6.830***	7.659***
	(11.352)	(1.147)	(1.993)
Constant	2.780***	1.047***	1.030***
	(0.251)	(0.027)	(0.045)
Observations*	1,964	1,964	1,964
R^2	0.002		
Adjusted R^2	0.002		
Log Likelihood		−5,647.478	−4,427.469
θ			2.062*** (0.095)
Akaike Inf. Crit.		11,298.960	8,858.938
Residual Std. Error	4.912 (df = 1962)		
F Statistic	4.744** (df = 1; 1962)		
Note:			*p<0.1; **p<0.05; ***p<0.01

* *We exclude stories not shared by this population.*

Table A.15: Tweet Volume vs. Positivity, Clinton-Only Followers

	Dependent variable:		
	Number of Tweets		
	OLS	*Poisson*	*negative binomial*
	(1)	(2)	(3)
Positivity	−15.712	−4.797***	−4.995**
	(12.960)	(1.453)	(2.353)
Constant	3.310***	1.196***	1.197***
	(0.116)	(0.013)	(0.021)
Observations*	1,964	1,964	1,964
R^2	0.001		
Adjusted R^2	0.0002		
Log Likelihood		−5,658.425	−4,432.053
θ			2.050*** (0.094)
Akaike Inf. Crit.		11,320.850	8,868.106
Residual Std. Error	4.916 (df = 1962)		
F Statistic	1.470 (df = 1; 1962)		
Note:			*p<0.1; **p<0.05; ***p<0.01

* *We exclude stories not shared by this population.*

Table A.16: Tweet Volume vs. Story Length, Sanders-Only Followers

	Dependent variable:		
	Number of Tweets		
	OLS	*Poisson*	*negative binomial*
	(1)	(2)	(3)
Story length	0.001***	0.0001***	0.0003***
	(0.0003)	(0.00001)	(0.00003)
Constant	2.995***	1.220***	0.992***
	(0.444)	(0.019)	(0.050)
Observations*	1,207	1,207	1,207
R^2	0.006		
Adjusted R^2	0.005		
Log Likelihood		−5,725.796	−2,972.025
θ			1.067*** (0.048)
Akaike Inf. Crit.		11,455.590	5,948.050
Residual Std. Error	9.527 (df = 1205)		
F Statistic	6.753*** (df = 1; 1205)		
Note:			*p<0.1; **p<0.05; ***p<0.01

* *We exclude stories not shared by this population.*

Table A.17: Tweet Volume vs. Emotionality, Sanders-Only Followers

	Dependent variable:		
	Number of Tweets		
	OLS	*Poisson*	*negative binomial*
	(1)	(2)	(3)
Emotionality	28.788	6.507***	10.285***
	(30.940)	(1.436)	(3.500)
Constant	3.347***	1.234***	1.160***
	(0.658)	(0.032)	(0.075)
Observations*	1,207	1,207	1,207
R^2	0.001		
Adjusted R^2	−0.0001		
Log Likelihood		−5,770.276	−2,991.602
θ			1.037*** (0.047)
Akaike Inf. Crit.		11,544.550	5,987.204
Residual Std. Error	9.550 (df = 1205)		
F Statistic	0.866 (df = 1; 1205)		
Note:			*p<0.1; **p<0.05; ***p<0.01

* *We exclude stories not shared by this population.*

Table A.18: Tweet Volume vs. Positivity, Sanders-Only Followers

	Dependent variable:		
	Number of Tweets		
	OLS	*Poisson*	*negative binomial*
	(1)	(2)	(3)
Positivity	−4.452	−1.141	−1.620
	(36.314)	(1.926)	(4.208)
Constant	3.915***	1.365***	1.366***
	(0.289)	(0.015)	(0.033)
Observations*	1,207	1,207	1,207
R^2	0.00001		
Adjusted R^2	−0.001		
Log Likelihood		−5,779.418	−2,994.452
θ			1.033*** (0.047)
Akaike Inf. Crit.		11,562.840	5,992.905
Residual Std. Error	9.553 (df = 1205)		
F Statistic	0.015 (df = 1; 1205)		
Note:			*p<0.1; **p<0.05; ***p<0.01

* *We exclude stories not shared by this population.*

Table A.19: Tweet Volume vs. Story Length, Cruz-Only Followers

	Dependent variable:		
	Number of Tweets		
	OLS	*Poisson*	*negative binomial*
	(1)	(2)	(3)
Story length	0.0003^{**}	0.0001^{***}	0.0001^{***}
	(0.0001)	(0.00001)	(0.00002)
Constant	2.028^{***}	0.745^{***}	0.734^{***}
	(0.142)	(0.023)	(0.035)
Observations*	1,495	1,495	1,495
R^2	0.004		
Adjusted R^2	0.004		
Log Likelihood		−3,406.008	−2,897.965
θ			2.455^{***} (0.153)
Akaike Inf. Crit.		6,816.015	5,799.930
Residual Std. Error	3.550 (df = 1493)		
F Statistic	6.357^{**} (df = 1; 1493)		
Note:			*p<0.1; **p<0.05; ***p<0.01

* *We exclude stories not shared by this population.*

Table A.20: Tweet Volume vs. Emotionality, Cruz-Only Followers

	Dependent variable:		
	Number of Tweets		
	OLS	*Poisson*	*negative binomial*
	(1)	(2)	(3)
Emotionality	5.332	2.233	2.393
	(9.653)	(1.723)	(2.451)
Constant	2.197***	0.789***	0.786***
	(0.209)	(0.038)	(0.054)
Observations*	1,495	1,495	1,495
R^2	0.0002		
Adjusted R^2	−0.0005		
Log Likelihood		−3,419.111	−2,904.432
θ			2.425*** (0.150)
Akaike Inf. Crit.		6,842.222	5,812.864
Residual Std. Error	3.557 (df = 1493)		
F Statistic	0.305 (df = 1; 1493)		
Note:			*p<0.1; **p<0.05; ***p<0.01

* *We exclude stories not shared by this population.*

Table A.21: Tweet Volume vs. Positivity, Cruz-Only Followers

	Dependent variable:		
	Number of Tweets		
	OLS	*Poisson*	*negative binomial*
	(1)	(2)	(3)
Positivity	1.934	0.841	0.895
	(11.361)	(2.107)	(2.941)
Constant	2.296***	0.831***	0.831***
	(0.095)	(0.018)	(0.025)
Observations*	1,495	1,495	1,495
R^2	0.00002		
Adjusted R^2	−0.001		
Log Likelihood		−3,419.850	−2,904.833
θ			2.423*** (0.150)
Akaike Inf. Crit.		6,843.700	5,813.665
Residual Std. Error	3.557 (df = 1493)		
F Statistic	0.029 (df = 1; 1493)		
Note:			*p<0.1; **p<0.05; ***p<0.01

* *We exclude stories not shared by this population.*

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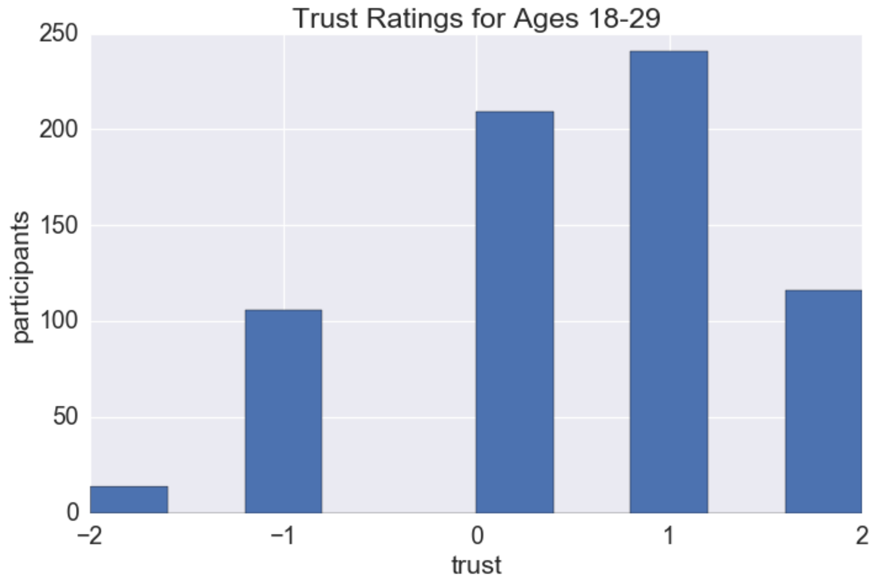
Appendix B

Figures


Trust Ratings for Ages 18-29
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100
150
200
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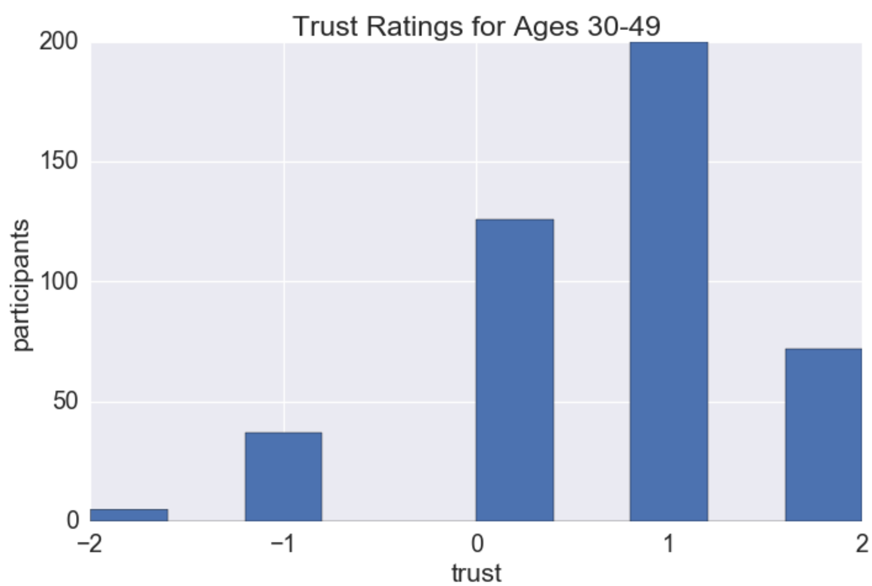
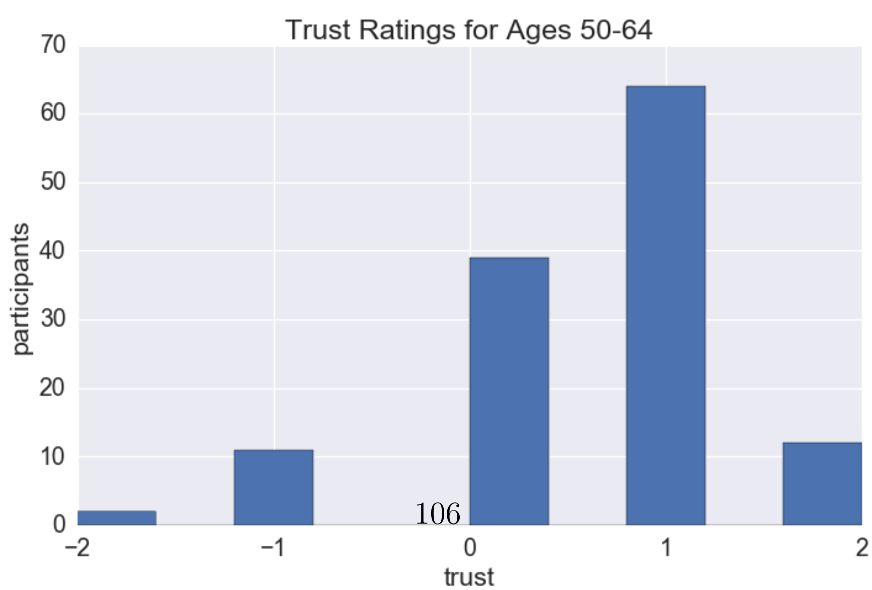
−1
0
1
2


Trust Ratings for Ages 30-49
participants
trust
0
50
100
150
200
−2
−1
0
1
2


Trust Ratings for Ages 50-64
participants
trust
0
10
20
30
40
50
60
70
−2
−1
0
1
2

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