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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The following people served as readers for this thesis:

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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 [26].

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 [19]. 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, this thesis 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 [26].

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 and author)? 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 [32, 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 trust and fairness rankings between high and low reading level stories.

From our findings in an experimental setting, we then extrapolate to another dimension of media: the social sphere of Twitter. In this dimension, we look for emotional signals in the text that cause it to become universally popular, with the goal of finding patterns cross party divides.

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 thesis hopes to shed new light on understanding what motivates readers' trust and distrust of news media, and pave pathways to understanding virality in the political news media.

Part I

Reading the News

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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" [29].

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. [22]

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 [24].

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 [19]. 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 [18].

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 [30]. 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 [16]. 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 [27]. 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 [31]. (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].

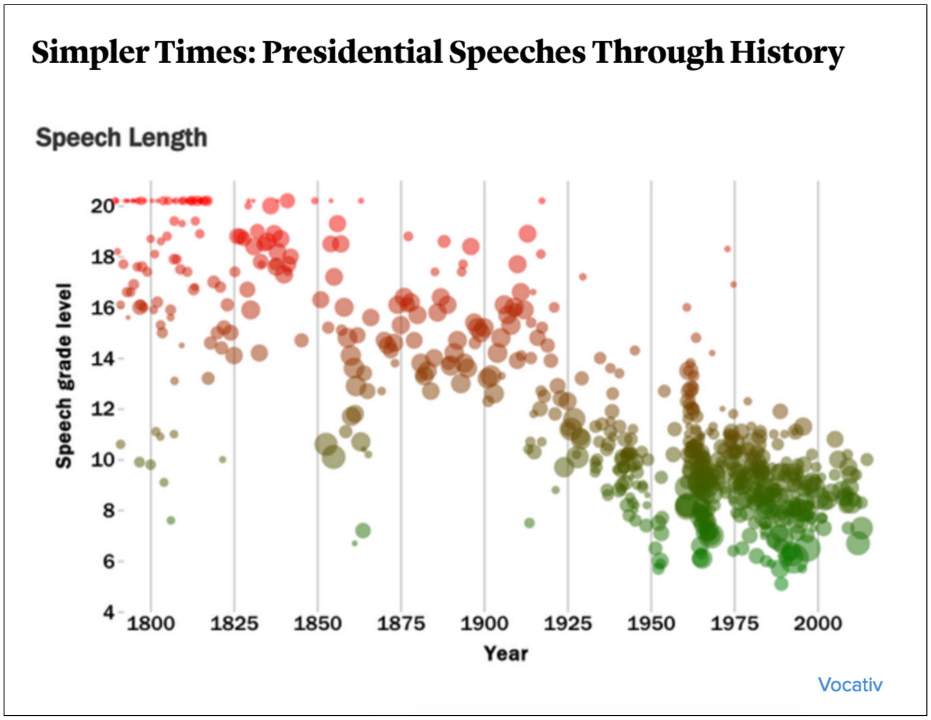

Figure 2-1: Language of Presidential Speech Decline

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 [32]. 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 [17].

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) [21]. 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 [23]. 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

Exploratory Study

I am not positive I will include the results of my first study in the thesis, but this is a placeholder. Also, I might include a chapter about "Patterns and Trends" at large with reading level and topic on the Electome dataset, for the analysis I did on that.

This might morph into an "additional data collection" portion for the Twitter analysis.

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Chapter 5

Study

5.1 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 six 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 the content.

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

And two verifying former theories:

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

- **H6**: Stories about candidates opposite to the readers preferred candidate score significantly lower in fairness, regardless of outlet.

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 [32].

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** and **H6**) to emerge.

5.2 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 5.1: 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 Study 2 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 [25]. 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.

5.2.1 Dataset

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

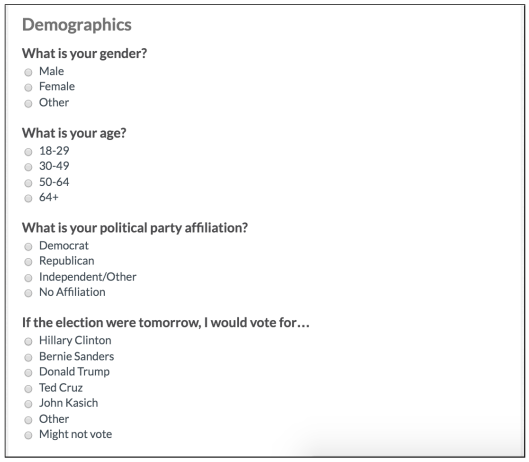
Reading level cutoffs were made by taking the bottom and top 25% percentile of Flesch-Kincaid scores for each candidate. From stories written by the Associated Press that made the cutoff, we formed pairs of high and low reading level stories from each topic. The topic with the highest distance between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

5.2.2 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.

Figure 5-1: 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

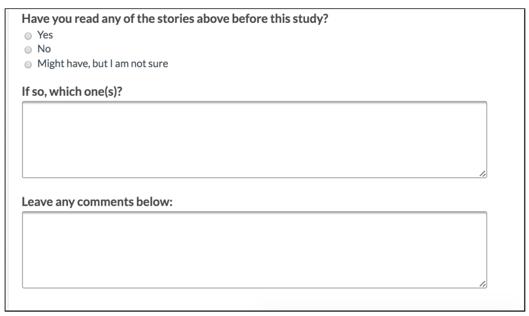
What is your age?
- 18-29
- 30-49
- 50-64
- 64+

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 5-2: Demographic Questions for Survey

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



Have you read any of the stories above before this study?
- Yes
- No
- Might have, but I am not sure

If so, which one(s)?

Leave any comments below:

Figure 5-3: 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.

5.2.3 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.

5.3 Basic Analysis

5.3.1 Demographics

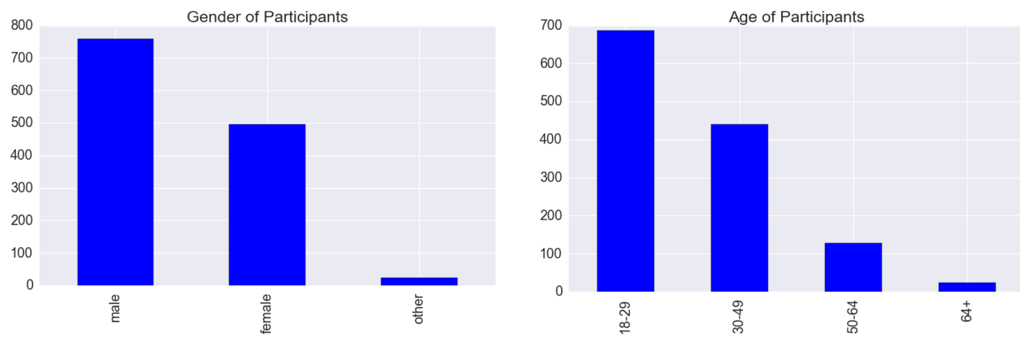


Figure 5-4: Demographics of Participants

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.

In our analyses, we balance for gender and age disparaties.

5.3.2 Location

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

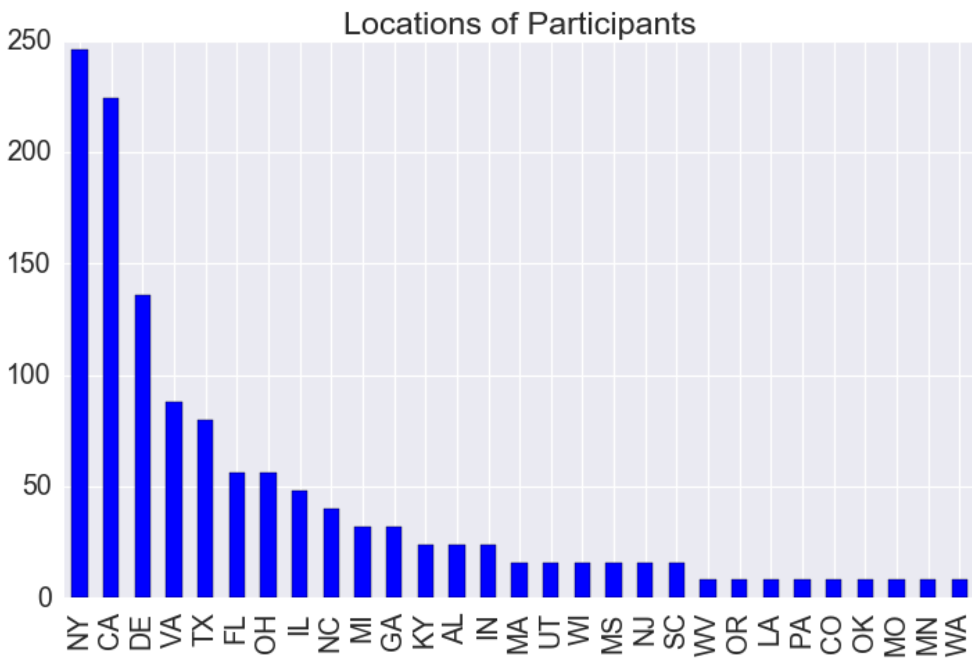


Figure 5-5: Locations of Participants

5.3.3 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.

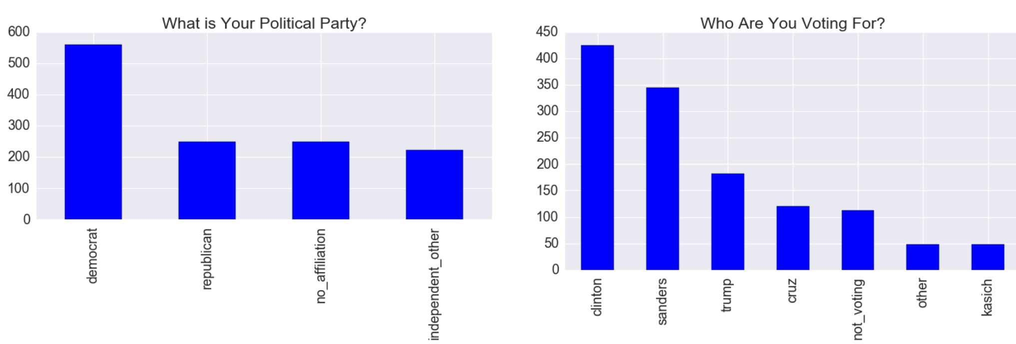


Figure 5-6: Political Affiliations of Participants

5.3.4 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 5-7: 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 13-1 on page 62.

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

For distributions of trust by party affiliation, see figure ?? on page ??.

5.3.5 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).

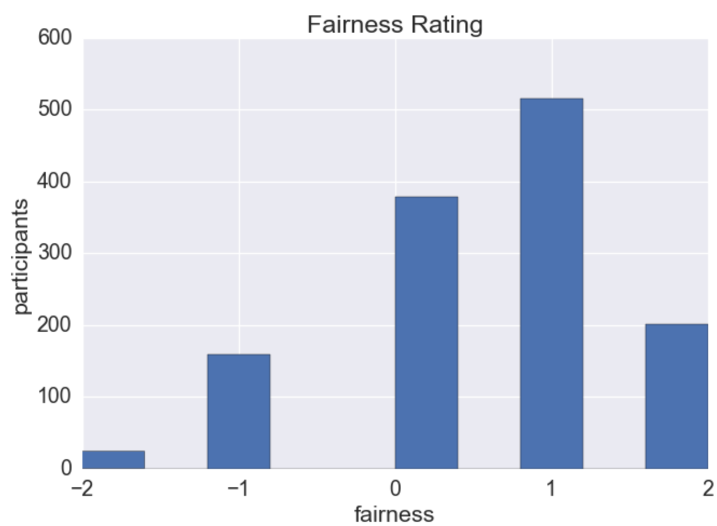


Figure 5-8: Overall Fairness Ratings

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" [20].

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Chapter 6

Findings

Table 6.1: 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.*

6.1 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.

6.2 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.

6.3 Qualitative

In our surveys, we left a space for people to leave comments about the task. Although most people did not fill out the question, here are some analyses of their responses.

To-do

6.4 Conclusions

To-do

6.5 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.

Part II

Sharing the News

Chapter 7

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.

7.1 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 has the ability to be broadcast and spread to millions of others in a real-time, public sphere.

7.2 Trust, Virality, and Controversy

So, Why does this matter? Well, in addition to sharing new content, social media acts as a megaphone for other (traditional) media. Finding these patterns between how people observe the trustworthiness of stories in a experimental setting and how they are shared on twitter can give insights to social media studies of the election, as we are doing in our group.

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Chapter 8

Metrics for Analysis

8.1 Independent Variables

8.2 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 [28]. 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.

8.3 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 *levels* of political engagement, we group those Twitter users who share news stories into three segments:

- *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)

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. We call each group X-followers where X is the candidate name, although these do not include every person on Twitter who follows X.

8.3.1 Who Are Single-Candidate Tweeters?

A qualitative peek into the characteristics of single-candidate tweeters shows a reasonable proxy for candidate loyalty. Examining the top 10 followers for each candidate by volume of tweets shared by each in our dataset, we see a mix of personal, organizational, and other accounts.

Below is a random sample of the profile descriptions of 10 single-candidate tweeters:

- *Clinton follower*: I write about climate change, Nikola Tesla, and Abraham Lincoln. Oh, and I'm an aquarium nut. Go figure.
- *Trump follower*: Trump supporter, free-lance writer, loves life, liberty & the pursuit of happiness
- *Sanders follower*: I am an Android. MUST NOT SLEEP; MUST WARN OTHERS
- *Clinton follower*: Love a little political humor? Then Letters From Us is the site for you. Check us out for new daily blogs and comics to feed your left-brain.
- *Trump follower*: I am a former Marine (E-5 Sergeant.)I am a proponent of eradicating a welfare state. I am appalled by the degradation of society by the liberal establishment

- *Trump follower*: We bring you the biggest breaking stories all over the world. We have online journalists that are experienced & caffeinated. with @JoshiiHD & DaviiHD

- *Clinton follower*: Media Critic/Journalist/Hillary 4 Am. Vol. Leader Prolific!!! Bad Manners Blocked! Blogs: https://t.co/KraI7CJNlD & https://t.co/WRcDx0bP63 #PDMFNB #UniteBlue

- *Sanders follower*: I am not accepting new clients. I am on vacation and not eligible to practice law until July 15, 2016.

- *Clinton follower*: Graduate of Delaware State, U of Penn, Bowie Md and Temple U

- *Cruz follower*: Conservative, Christian, Farm wife to @1861_again, Stay at home mom of 3 boys, Gardner, Altrium health suppliment dealer, Strict Constitutionalist, Former Nurse

Chapter 9

Analysis

9.1 Dataset

9.2 Connecting Tweets with Stories

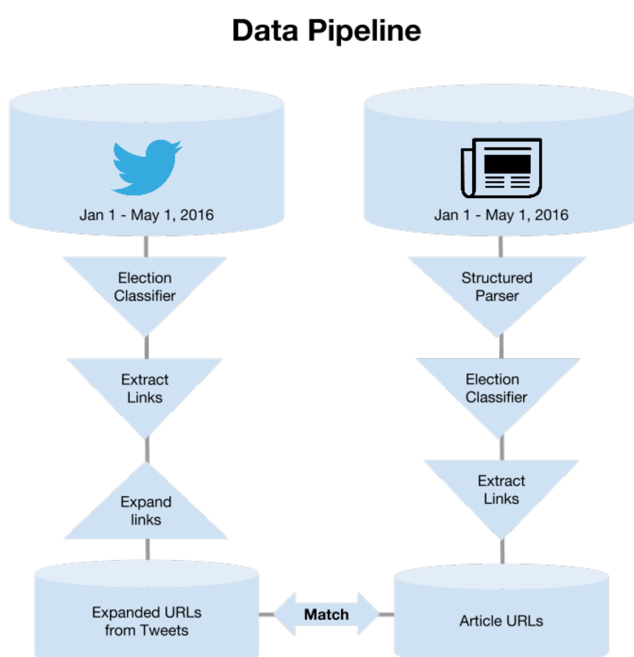

Figure 9-1: Data Pipeline

9.2.1 URL Extraction

9.2.2 Mapping Tweets to Stories

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Chapter 10

Future Directions

We found these effects, so what?

10.1 Designing Interventions

This section I plan to create suggestions for interventions (i.e. now that we know what makes people not trust news... so what?) on how to get people to read a diverse set of news media with high trust.

10.2 De-biasing Twitter Analysis

This section I plan to create suggestions for interventions (i.e. now that we know what makes people not trust news... so what?) on how to get people to read a diverse set of news media with high trust.

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Chapter 11

Conclusion

Media distrust, which has intensified over the last two decades, is a phenomenon with serious implications in the practice of democracy and a well-informed public.

In an election year prefaced by deep cynicism towards American institutions (a 2015 survey showed that just 19% of the population trusts the federal government), attitudes towards the news media fare no better. Almost two-thirds of Americans think that the national news media is a negative influence on the country [6].

Our results confirm previous hypotheses about the importance of the role of the reader in determining news trust and bias *over* the role of the content itself. We show that drastically different use of language complexity has little effect on the reader in comparison to the presence of media brands.

Interestingly, although showing media from outlets of opposing political orientations decreases trust and fairness perceptions in the reader, when no outlet is attributed to the story, trust in the story also decreases. This suggests that interventions designed to *level* news stories by aggregating them without attribution to source might not be effective in creating a balanced news diet for sustaining informed voters.

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Chapter 12

Tables

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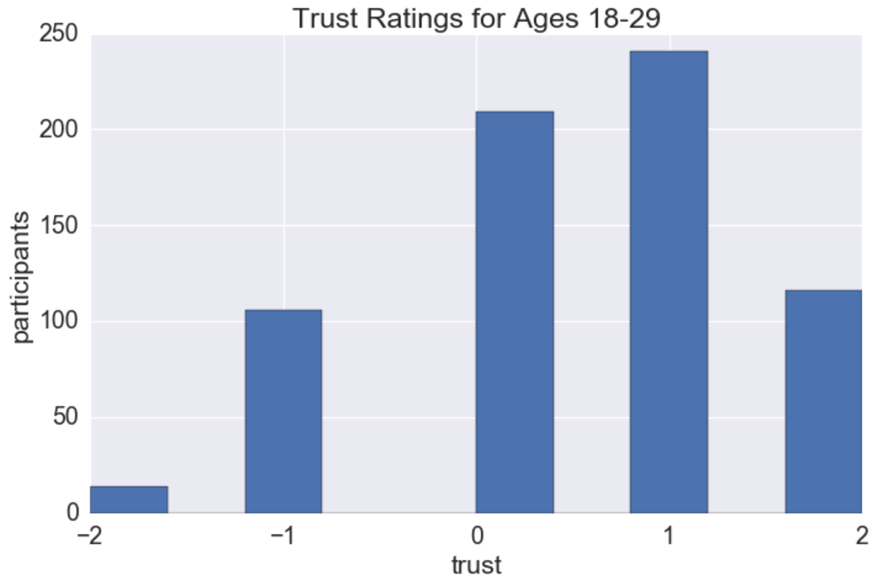
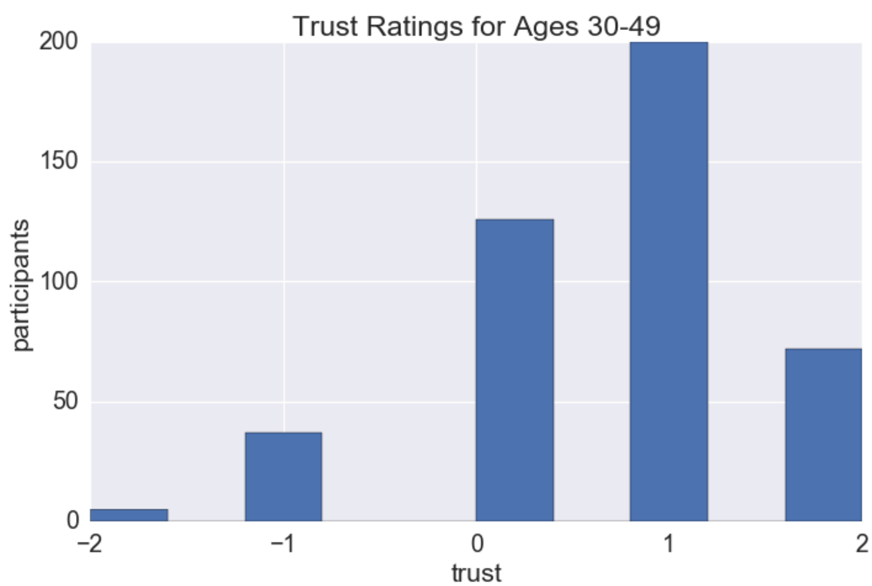
Chapter 13

Figures


Trust Ratings for Ages 18-29
participants
trust
0
50
100
150
200
250
−2
−1
0
1
2


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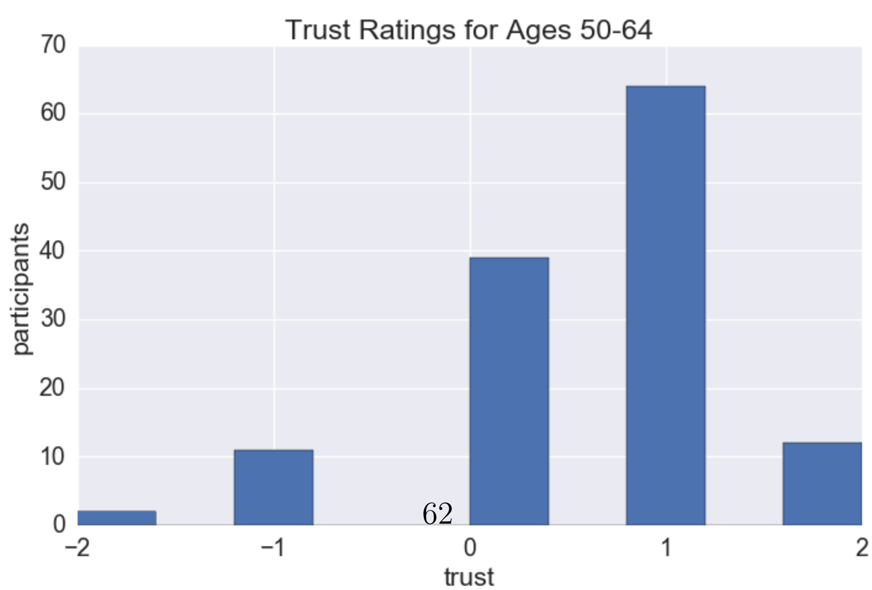
50
100
150
200
−2
−1
0
1
2


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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